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STATISTICAL PROCESS CONTROL FOR TOTAL QUALITY

The Engineering and Fabrication Branch of the Technical Services Department provides a wide range of engineering, design, and fabrication services for the Applied Physics Laboratory. The Branch routinely practices a technique known as "statistical process control" in the design, fabrication, testing, calibration, and quality control phases of its work to ensure the quality of designed and fabricated parts.

INTRODUCTION

Statistical process control, one of the major quality techniques being emphasized as part of the resurgent focus on quality in this country, has gained wide acceptance among quality control experts. The long-term benefits of this technique are increased communications among all departments, better insight into cost reduction, continuous quality improvement, and a more effective design and fabrication interface.

The "total quality" process is a never-ending endeavor to add new value to a product or service. This total quality approach presents a sharp contrast to the detection/inspection mode of quality control prevalent in industry over the last four decades, a mode that is costly and does not enhance either product or service.[1]

In the emerging total quality environment, a fundamental understanding of all processes is essential for continuous improvement. The objective of Total Quality Management (TQM) is to broaden the focus of quality to embrace the concept of a continuous improvement process as a means by which an organization creates and sustains a positive and dynamic working environment, fosters teamwork, applies quantitative methods and analytical techniques, and taps the creativity and ingenuity of all its people. As defined by the Department of Defense,

Total Quality Management (TQM) is both a philosophy and a set of guiding principles that represent the foundation of a continuously improving organization. TQM is the application of quantitative methods and human resources to improve the material and services supplied to an organization, all the processes within an organization, and the degree to which the needs of the customer are met, now and in the future. TQM integrates fundamental management techniques, existing improvement efforts, and technical tools under a disciplined approach focused on continuous improvement.[2]

A number of technical tools and techniques are used in the process of implementing TQM. Most of these tools are oriented to a certain type of activity, and all have their specific strengths and weaknesses. These TQM tools include

Benchmarking
Cause-and-effect diagrams
Nominal group techniques
Quality function deployment
Pareto charts
Histograms
Concurrent engineering
Design of experiment
Shewhart cycles
Just-in-time delivery
Statistical process control

The purpose of this article is to explain, in broad terms, the techniques and applications of "statistical process control." Examples of control charts used in the Poseidon program of the NASA ocean topography experiment (TOPEX) and a brief discussion of Taguchi methods are also included.

DEFINING A PROCESS

Any process can be understood as a series of operations during which a "value added" activity is performed at each subsequent step. A process is therefore the transformation of a set of inputs, which can include but is not limited to methods, people, materials, and machines, that results in some output, such as products, information, or services. The total performance of the process—the quality of its output and its productive efficiency—depends on the way the process has been designed and built and on the way it is operated. In each area of every organization, many processes are taking place simultaneously. Every task throughout an organization must be viewed as a process. To bring the system under control, the variables affecting the output must be reduced (see Fig. 1).[1]

In other words, the key to improving quality is to improve the system, and one way to do that is to control the processes. The terms "feedback control systems," as used in system analysis and industrial technology, and "control of processes," for measurements of variations, are interrelated. Process control is a part of the feedback control system. Feedback control systems influence every facet of modern life, from chemical process plants,
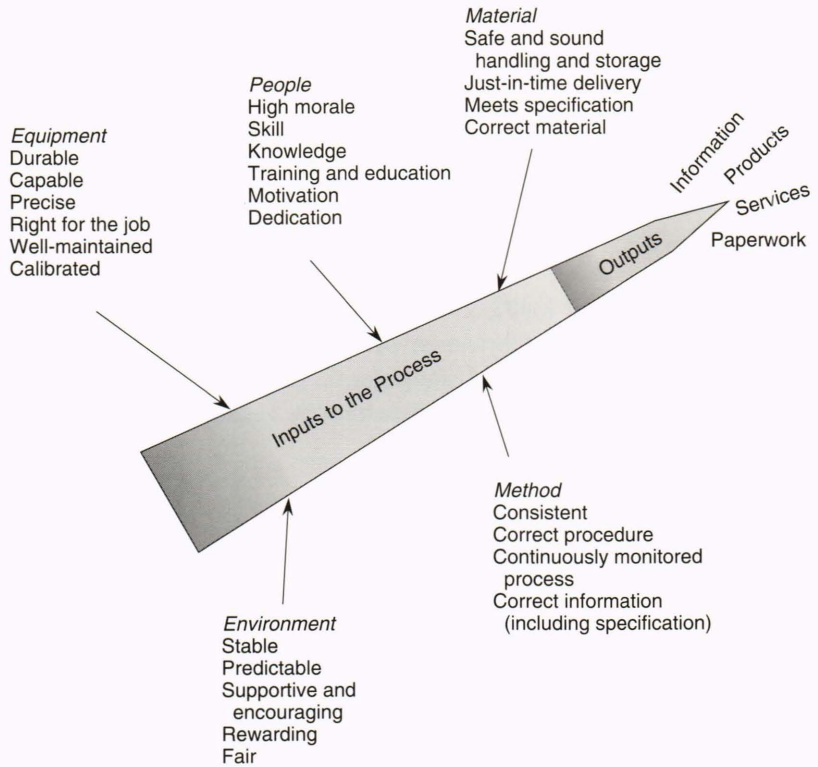
Figure 1. Typical input and output variables that contribute to a process.

navigational and guidance systems, space satellites, and pollution control, to the mass transit system. In the broadest sense, a feedback control system is any interconnection of component designs to provide a desired output on the basis of a feedback of prior system information. For example, the portion of a system that is to be controlled is called the "plant" and is affected by applied signals called "inputs," which produce signals of interest called "outputs." Whether the plant is an electrical generator or a nuclear reactor, it is the designer's job to ensure that the plant operates as required by using a "controller" to produce a desired behavior.[3]

In process control, as in feedback control, data are collected and appropriate action is taken to control the quality of the process and the product on the basis of the analysis of measurements.

THE CONCEPT OF VARIATION

One of the fundamental aspects of nature is that events or physical objects are not precisely repeatable time after time. One of the characteristics of modern manufacturing is that no two pieces are ever made exactly alike. The variations may be small, for example, as for gage blocks, which have been guaranteed to two-millionths of an inch. Whether large or small, variations exist in parts manufactured in all fabrication processes. Regardless of whether parts are fabricated by numerical control machine tools, annealing furnaces, painting machines, or tools for potting and encapsulation of delicate electronic components, some variations always occur. The sources of variation are many. They include

People (the way they perform their duties)
Equipment (adjustments and conditions)
Material (uniformity)
Methods (the processes used)

The amount of basic variability will depend on various characteristics of the process.

Joseph M. Juran and W. Edwards Deming, and other renowned quality professionals, cite two major types of variation that cause quality problems: common causes and special causes. Common causes are system problems present in every process owing to a combination of people, materials, machines, methods, and the environment. Examples are poor product design, improper materials, inadequate training, or unsatisfactory working conditions. The common causes of variations can be isolated through detailed analysis, and resolution of these causes usually requires action on the system. Special causes are unusual occurrences in a process that are unpredictable, such as problems with materials, machines, or individuals. Special causes of variation can be detected by statistical techniques and are not common to all operations involved. The discovery of a special cause of variation and its removal are usually the responsibility of someone who is directly connected with the operation.[4]

A process affected only by common causes is called a stable process. The system for a stable process remains essentially constant over time. This system stability does not mean that no variation occurs in the outcome—it simply means that the variation is very slight and that the outcome still meets requirements. A stable process implies only that the variation is predictable within statistically established limits.

STATISTICAL PROCESS CONTROL

Statistical process control (SPC) provides a method for controlling variability that affects quality characteristics in fabrication processes. As a technique for implementing process control using modern statistical tools and techniques, SPC fosters quality while the product is being produced, not afterwards. The goal of SPC is to generate the highest possible degree of consistency in any process through the collection, analysis, and interpretation of data. Statistical process control is a formalized system for paying attention to detail using mathematics (statistics) to study a set of causes (the process) in order to stabilize, monitor, and improve production (i.e., better control). The effects of a working SPC system are to continuously improve the process through closer targeting and to reduce variability. Continuous process improvement lowers cost while assuring consistent quality and reliability.

The goals of SPC are as follows:

1. To achieve consistency by reducing overall variation in the process by implementing corrective action.

2. To simplify procedures, methods, and tools.

3. To measure the long-term performance level after the process has been brought under control.

4. To obtain the best performance from current equipment without major capital expenditure.

5. To provide information for better cost estimation, feedback, a common language for discussing process performance, and reliable permanent records and reports of actual performance.[5]

CONTROL CHARTS

In the 1920s, Walter Shewhart of Bell Laboratories first developed a way to take data from a process and prepare a graph. On the basis of this graph (known today as the "P" chart), he is credited with the development of the theory and application of control charts. Since then, control charts have been used successfully in a wide variety of process control situations in the United States and other countries.[6]

A control chart can be thought of as a traffic signal, the operation of which is based on evidence from a small sample, usually consisting of more than one individual measurement, taken at random from a process. The variations of any characteristic are quantified by sampling the output of the process and estimating the parameters of its statistical distribution. Changes in the distribution are revealed by plotting these estimates versus time.

The most frequent type of variation encountered in the workplace can be described by a normal distribution, also called a bell-shaped, or Gaussian, distribution.[7]

The standard deviation as a measure of dispersion takes into account each of the data points and their distance from the mean. The more dispersed the data points, the larger the standard deviation will be. The population standard deviation is computed as the square root of the average squared deviation from the mean and is denoted by σ.

For analytic studies where the conceptual population cannot be measured, the value is estimated by the standard deviation of the sample (or subgroup) of n observa-tions. The sample standard deviation (S) is the square root of the sum of the squares of all the individual readings, minus the square of the average of those readings, $\overline{X}$, divided by the sample size minus one, and is a measure of the dispersion of those individual readings. Expressed mathematically,[8]

$$S = \left[\frac{\sum (X - \overline{X})^2}{n - 1} \right]^{1/2} .$$

Although the sample standard deviation is the most widely applied standard deviation measure in many manufacturing operations, the population standard deviation measure is also very important in such applications as the evaluation of the ongoing quality of a continuous process and the long-term quality of vendor shipments over time.

Control Charts for Variables

There are two types of control charts: variable and attribute. Control charts for variables are powerful tools that can be used when measurements from a process are available. Variable charts explain process data in terms of both spread (piece-to-piece variability) and location (process average). Control charts for variables are prepared from quantitative data where measurements are used for analysis, such as the diameter of a bearing journal in millimeters, the closing effort of a door in kilograms, the concentration of an electrolyte in percent, or the torque of a fastener in newton meters.

Control charts for variables are prepared and analyzed in pairs, where one chart is for location and the other is for spread. The most commonly used pair of control charts consists of an $\overline{X}$ and an R chart, where $\overline{X}$ is the average of the values in small subgroups (i.e., a measure of location) and R is the range of values within each subgroup calculated by subtracting the smallest number in a sample set from the largest number (the measure of spread).

Charts of $\overline{X}$ and R are developed from measurements of a particular characteristic of the process output. These data are reported on small subgroups of constant size, usually from two to five consecutive pieces, where subgroups are taken periodically (e.g., once every twenty minutes or four times per shift). To be most effective, a data-gathering plan should be developed and used as a basis for collecting, recording, and plotting the data on a chart. The selection of the number of subgroups should be made to assure that the major sources of variation have had an opportunity to appear. From a statistical standpoint, twenty-five or more subgroups containing about 100 or more individual readings give a good test for stability, and if the process is stable, they give good estimates of the process location and spread.

For example, a sample of twenty-five subgroups, consisting of four pieces each, is shown in Table 1. The first step in constructing the $\overline{X}$ and R charts is to find the average of all the averages, called the "grand average" and written as $\overline{\overline{X}}$. The grand average represents the average of all the measurements. The range chart is constructed in a manner similar to the average chart. The average range is written as $\overline{R}$. The upper and lower control limits for constructing the control charts are

Table 1. Control chart showing twenty-five subgroups, each containing four samples of tensile strength, with calculated average and range.

Subgroup	Sample measurements 1	2	3	4	$\overline{X}$	R
1	14	10	12	13	12.25	4
2	14	12	15	10	12.75	5
3	10	11	10	11.5	10.63	1.5
4	12	15	17	14.5	14.63	5
5	13	8	10	11.5	10.63	5
6	8	10.5	9	11	9.63	2
7	11	12.5	9	8	10.13	4.5
8	16	15.5	13	15	14.88	2.5
9	16	13	10	20	14.75	10
10	10	11	15	15	12.75	5
11	18	15	14.5	16	15.88	3.5
12	15	13	13.5	12	13.38	3
13	14	19	13	12	14.50	7
14	16	18	11	11	14.00	7
15	16	16	15	15	15.50	1
16	16	15.5	10	14	13.88	6
17	16.5	18	18	20	18.13	3.5
18	15	18	18	16.5	16.88	3
19	13	16	17	15	15.25	4
20	16	18	17.5	19	17.63	3
21	18	17	13	14	15.50	5
22	16	10.5	10	16	13.13	6
23	15	16	15	13	14.75	3
24	11.5	14	15	10	12.63	5
25	16	12	15	16	14.75	4

Note: All measurements are in pounds of force per square inch.

generally set at the mean, ±3 standard deviations. The control charts for averages and ranges are illustrated in Figure 2. Calculations for the control charts are as follows (all values are in pounds of force per square inch):
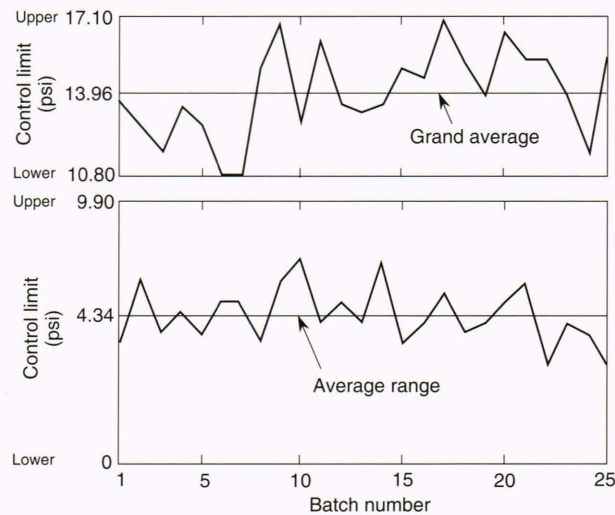

Figure 2. Plotted data points for the average (top) and range (bottom) data calculated and presented in Table 1.

For $\overline{X}$,

$$\text{Upper control limit} = \overline{\overline{X}} + (A_2 \times \overline{R})$$
$$= 13.96 + (0.73 \times 4.34)$$
$$= 17.1$$

$$\text{Lower control limit} = \overline{\overline{X}} - (A_2 \times \overline{R})$$
$$= 13.96 - (0.73 \times 4.34)$$
$$= 10.8$$

The central line, $\overline{\overline{X}}$, is 13.96.

For R,

$$\text{Upper control limit} = D_4 \times \overline{R}$$
$$= 2.28 \times 4.34$$
$$= 9.9$$

$$\text{Lower control limit} = D_3 \times \overline{R}$$
$$= 0 \times 4.34$$
$$= 0$$

The central line, $\overline{R}$, is 4.34. Here A_2, D_3, and D_4 are factors that depend on subgroup size (see Table 2):[9] A_2 is the factor for control limits for averages, and D_3 and D_4 are the factors for control limits for ranges.

Control Charts for Attributes

Although control charts are most often thought of in terms of variables, versions have also been developed for attributes. Attribute-type data have only two values (e.g., pass/fail, conforming/nonconforming, go/no go, present/absent), which are all counted for recording and analysis. Examples include such characteristics as the presence of a required label, the installation of all required fasteners, or the absence of errors on an expense report. Almost all data gathered for management summary reports are in attribute form.

Several types of attribute control charts exist, including the following:

1. P charts for measuring the proportion of nonconforming units from samples that are not necessarily of constant size. An example is the fraction of bad welds in a day's fabrication in APL's sheet metal shop.

Table 2. Dependence of $\overline{X}$ and R control chart factors on the number of samples in a subgroup.

Number of samples	$\overline{X}$ chart factor A_2	R chart factors D_3	D_4
2	1.88	0	3.27
3	1.02	0	2.57
4	0.73	0	2.28
5	0.58	0	2.11
6	0.48	0	2.00
7	0.42	0.08	1.92
8	0.37	0.14	1.86
9	0.34	0.18	1.82
10	0.31	0.22	1.78

2. The np chart for measuring the number of nonconforming operations from samples of constant size. An example is undersize spot welds in a housing assembly.

3. U charts for measuring the number of nonconformities per unit from samples that are not necessarily of constant size. An example is the number of people absent in one day.

4. C charts for measuring the number of nonconformities in inspection lots of constant size. These charts are applied to two major types of inspection situations: (1) where nonconformities are scattered through a more-or-less continuous flow of products, and (2) where nonconformities from many different potential sources may be found in a single unit. An example of the first type of C chart is the number of air bubbles in a sheet of glass; an example of the second type is a vehicle inspection.

Generally, the attribute charts are placed at or near the end of a process, and the opportunity for prevention of defects is less. The earlier in the process that the chart is placed, the greater the impact is. The difference between $\overline{X}$ charts and P, np, C, and U charts is that $\overline{X}$ charts track variable data by tracking the process rather than the attributes of a process or a combination of processes. An $\overline{X}$ chart can reveal more about the quality of products being fabricated, and the power behind SPC comes from analyzing the charts and making refinements. Another important distinction is that charts of variables tend to provide more information with fewer observations than do charts of attributes.

The charting of variables is also essential for continuous improvement of processes whenever it is economically justified. Attribute charting tracks the number of defects or the percentage of defects but does not relate the degree to which those products are defective or good. It is that extra degree that enables much more information to be read from variable charting, that is, to determine how close something is to the optimal value.

USE OF CONTROL CHARTS TO ANALYZE TOPEX PARTS

To assure hardware quality, the Engineering and Fabrication Branch (TEO) uses a series of control charts designed specially for very short fabrication runs. This type of control chart is suitable for frequent machine changeovers and setups to accommodate many different parts with similar characteristics that undergo the same fabrication process.

The control chart used in TEO is called a NOM–I–NAL chart. The special feature of this chart is the coding of the measured reading as variations from a common reference point. Charts of this type were used by TEO in analyzing parts fabricated for the TOPEX Poseidon program. The primary function of NASA's TOPEX program is to improve our understanding of global ocean dynamics by making precise and accurate observations of the oceanic topography. The Laboratory supplied the TOPEX satellite with its primary sensor, a dual-frequency radar altimeter, a laser retro-reflector array, and an ultrastable frequency reference unit.

A total of 190 spacers with seven different part numbers were fabricated by TEO for the TOPEX program. All characteristics of these parts were identical, except for their length.

The reference point for these spacers was the nominal drawing dimension for the length, and the nominal value is the zero point on the $\overline{X}$ chart. All parts were plotted on the same control chart, allowing the inspector to continuously monitor the machine behavior through all part changeovers. The sample size was three spacers. Analysis of two of the seven types of spacers is described in the following discussion, where all measurements are given in inches.

Spacer A

The length specification for spacer A was 0.230 to 0.240, and the nominal value was 0.235.

Actual	Nominal	Variation from nominal
0.231	0.235	−0.004
0.233	0.235	−0.002
0.232	0.235	−0.003

The sum of the variations ($-0.004 + -0.002 + -0.003$) is -0.009, $\overline{X}$ is -0.003, and R is 0.002.

Six consecutive samples of three spacers were drawn and their $\overline{X}$ and R values were plotted on the chart before the machine was readjusted to run spacer B; the only change was the nominal value.

Spacer B

The length specification for spacer B was 0.340 to 0.350, and the nominal value was 0.345.

Actual	Nominal	Variation from nominal
0.347	0.345	+0.002
0.345	0.345	0.000
0.346	0.345	+0.001

The sum of the variations for spacer B (0.002 + 0.000 + 0.001) is 0.003, $\overline{X}$ is 0.001, and R is 0.002.

The $\overline{X}$ and R values were plotted on the chart, and the machine was readjusted to run spacer C. When twenty-five samples had been taken (three pieces per sample) and plotted, the control limits were calculated with the traditional formulas given previously, using coded values.

Control limits and center lines were drawn on the NOM–I–NAL chart (Fig. 3). The range chart exhibits a steady state of control. If the variability in the range chart had been high, it could have been the result of one of the following:

1. Control limits improperly established.
2. A change in raw material.
3. A change in the process.
4. Equipment or tooling that had become worn.
5. Operator error.

The NOM–I–NAL chart technique assumes that the process distribution for each of the different parts has approximately the same dispersion (standard deviation). If a part has a different standard deviation, the range chart will show a run (six or more consecutive points on one
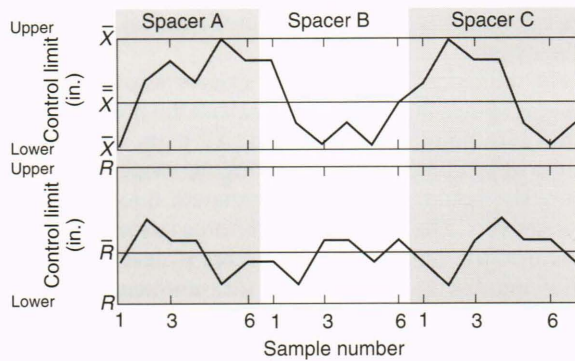
Figure 3. A NOM–I–NAL control chart for averages (top) and ranges (bottom) in a short-run fabrication process.

side of $\overline{R}$) during the time that part is being fabricated. The part must be plotted on a separate chart to be monitored correctly.

The NOM–I–NAL chart has proved effective in controlling a family of similar parts run over the same machine when the lot sizes are very small. This new technique minimizes the number of control charts and charting efforts required and maximizes the amount of information about the behavior of the process.

The NOM–I–NAL chart for short runs was developed in 1986 at the International Quality Institute (IQI) by Davis R. Bothe. Since that time, about 800 organizations, including various research and development organizations, have used and approved these charts. The American National Standards Institute (ANSI) has also recognized this charting system and has included it as a supplement to their standards.

IMPLEMENTATION OF STATISTICAL PROCESS CONTROL

Successful implementation of ongoing, effective SPC requires a realistic and practical approach. With proper planning, it should be able to be implemented in a real-world organization comprising various groups with competing problems and priorities. One of the conditions deemed necessary for SPC to work is continuous education and training. An overall strategy, including an evaluation of needs, a clear description of pertinent concepts, meaningful application opportunities, and follow-up to ensure effective use of concepts, is an absolute requirement for success.[10]

The checklist for SPC implementation is broken into four phases.

Phase One

The first phase of SPC implementation is the most important. It requires three actions:
1. Defining the project.
2. Assigning responsibilities.
3. Scheduling implementation.

An implementation plan to achieve the objectives should be provided in detail. Successful completion of this phase will require the serious commitment of resources and active involvement of all team members.

Phase Two

The second phase of implementation consists of five steps:
1. Collection of data.
2. Review of historical process and product data.
3. Review of equipment maintenance records.
4. Review of fabrication procedures.
5. Conduct of a process capability study.

The process capability study is a systematic procedure for determining the natural or inherent variation in a process and is used to measure and evaluate the true capability of a process. Process capability studies demonstrate whether or not the process is actually capable of meeting specifications.

Data collection and process capability studies establish the necessary context for SPC (i.e., reviewing process history and equipment maintenance). In addition to using the data collected to control the process, the team members study how to improve the process. They also analyze the data by using the SPC methods taught in the training sessions. Establishing and setting priorities for the specific, quantifiable measures of improvement ensure that SPC is more than just the introduction of some statistical tools; the tools are those from which constructive decisions can be made.

Phase Three

The third phase of SPC implementation focuses on the effective use of data, and also consists of five steps:
1. Determination of the most effective sampling scheme.
2. Elimination of unnecessary data collection.
3. Preparation of control charts.
4. Initiation of a control feedback scheme for corrective action.
5. Documentation of changes to the current procedure.

A strong emphasis is placed on eliminating unnecessary data collection during this phase, a key to earning the endorsement of employees and management and allowing them to focus their efforts on the significant aspects of the problem. Feedback schemes and documented corrective procedures are strongly emphasized.

Phase Four

The fourth phase of implementation consists of four parts:
1. Introducing SPC across all areas for continuous improvement.
2. Monitoring effectiveness so the control scheme can be updated.
3. Performing continuous auditing of the process.
4. Maintaining the SPC record.

In this phase, specific objectives must be focused upon immediately, and responsible corrective action is needed to retain SPC for the long term. Continuous process audit and SPC documentation are needed to ensure reinforcement of the corrective action efforts.

Some caution must be exercised when implementing SPC in any process. Two kinds of error must be avoided: (1) taking unnecessary actions on a stable process (i.e., tampering, overadjusting), or treating common cause sources as if they were special causes; and (2) failing to

respond to process variations, or responding to special causes as if they were common causes.

Some pitfalls to successful implementation of SPC include the following:

1. Making a short-term commitment (failure to stay on course).

2. Using a haphazard approach (a little of this, a little of that, with no meaningful change in the system).

3. Failing to solicit worker input.

4. Measuring success and guiding a program on the basis of short-term profit.

5. Putting emphasis only on the production of control charts (charting for show only).

6. Charting with inadequate data that do not lead to corrective action (data are useless unless they initiate action to eliminate defects).

Although conditions vary among organizations, the nature of the challenges is common to almost every organization considering SPC implementation. The four-phase implementation checklist provides a framework for ensuring that SPC will actually be used on the shop floor, and each phase is designed to deal with one or more of the challenges that design and fabrication environments routinely pose to SPC implementation. Training and implementation of SPC in various groups of TEO are currently in full progress.

After undertaking the SPC effort, some very real benefits begin to emerge. Probably, the biggest of these is the increased communication between design and fabrication groups. When both groups compare how well fabrication is controlling the process and how well design has chosen its tolerance with respect to machine capability, SPC is worth the effort.

THE TAGUCHI METHOD

Genichi Taguchi, a leading Japanese engineer and management consultant, developed methods for SPC that are described in a 1981 Japanese standards association publication entitled "On-Line Quality Control During Production." Some of his methods are very simple, practical, and useful.

Dr. Taguchi formed his techniques of product and process development to optimize designs by minimizing loss (cost), improving consistency of performance, and creating robust products. A robust design is one that is sound and reliable and capable of performing its function under a wide range of conditions and environments. Robust designs are less sensitive to variation in parts, processes, and operating environments. The Taguchi methods include a technique for estimating the loss associated with controlling or failing to control process variability. Traditional approaches to design and fabrication stress compliance with specifications. The ideal "target" value that will translate into the most robust product and produce the highest customer satisfaction should be some fixed value within the specification limits. As long as products fall within the specification limits, as illustrated by points a and b in the top diagram in Figure 4, they are considered equally "good." If a product falls outside the limits, as shown by point c, it is automatically "bad." Observation and common sense inform us that the difference between

the good (point b) and the bad (point c) can be slight, and distinction between them is somewhat arbitrary. Likewise, the difference between points a and b makes it clear that they are not equal and that point b, which is farther from the target value, must be in some sense less "good."

The Taguchi method uses statistical techniques to compute a "loss function" (bottom diagram in Fig. 4), which can be used to determine the cost of producing the products that fail to achieve a target value. This procedure is also useful for determining the value or break-even point of improving a process to reduce variability. If a target value is indeed an ideal value, product performance will degrade as a function of any deviation from the target. The result may be lower reliability, less accurate performance, or less tolerance of the environment in which the product is used. Basically, Taguchi's approach consists of developing a model or loss function that attempts to optimize the process by minimizing the losses. Taguchi strongly believed in quantification of information and its analysis through statistical methods.

Mathematically, Taguchi's loss function is represented by

$$L = K (Y - T)^2 ,$$

where L is the monetary loss, K is a cost constant, and Y is the location of a given item with respect to the target T. In this equation, Y is the performance of a product and T is the corresponding target value. Loss is therefore defined as a constant times the square of the deviation from the target.

Several different engineering techniques for producing more robust designs are included in the Taguchi methods. One of these techniques is called the "design of experiments." This technique is an investigation of the effects of, and interactions among, selected design parameters
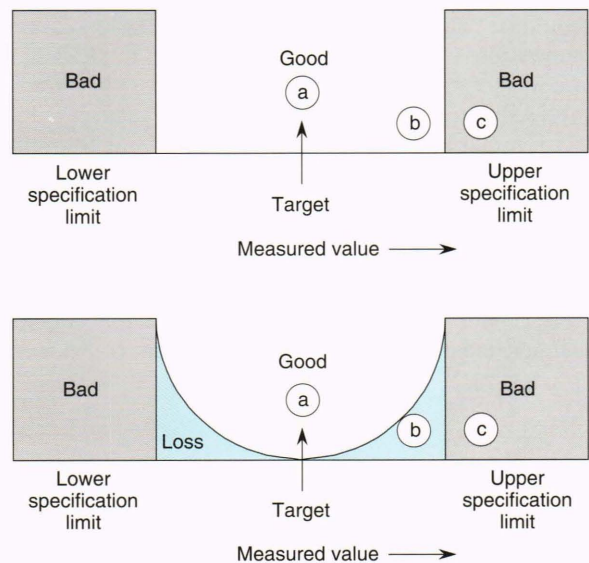

Figure 4. Comparison of the traditional approach to product variability (top) and Taguchi's technique for estimating the loss associated with failure to control variability (bottom).

and permits engineers to choose among design alternatives on the basis of a minimum number of controlled tests. This design technique improves the design-to-production transition, quickly optimizing product and process design, reducing cost, stabilizing processes, and desensitizing variables.

The design and analysis of experiments has many applications:

1. To compare two machines or methods.
2. To study the relative effects of various process variables.
3. To determine the optimal values for process variables.
4. To evaluate measurement system errors.
5. To determine design tolerances.
6. To select the optimum combination of materials.[2]

The combination of robust design and lower variability improves the process and yields the most competitive products.

CRITICISM OF TAGUCHI METHODS

Taguchi's loss function assumes that the target is correct and that the loss function is realistically approximated by sums of squared distances from the target. That is not always true. In addition, the consequences of being on the low side of the target can be much more devastating than being above the target. Weak fibers, for example, result in fabric wear and fatigue that lead to customer dissatisfaction. On the other hand, strong fibers may cost a little more but lead to customer satisfaction and repeat sales.

This criticism is minor, however, compared with Taguchi's contribution. His thinking is correct and fundamental to the concept of continuous improvement. It expresses deviation from the target in terms of cost, since the quality loss function is used as an evaluation tool during both parameter and tolerance design to assure cost-effective decision making.

The Taguchi approach has several advantages over the traditional statistical experimentation. Basic Taguchi methods are easy to learn, teach, use, and implement in an engineering/manufacturing environment and provide an effective cost-comparison measure that can be used for decision making. Taguchi appeals to the common sense approach of doing things. The Taguchi approach, moreover, is technological rather than theoretical, and no obvious assumptions are stated before data analysis.

The disadvantages of Taguchi methods run parallel with the advantages of traditional experimentation. Because model building is not practiced within Taguchi methods, factor levels can only be set at one of the levels chosen to run the experiment, increasing the risk of not finding the ultimate optimal solution.

Traditional statistical experimentation is an excellent tool when used to determine cause-and-effect relationships and to develop a complete understanding of all system processes. One major drawback is the complexity of statistical analysis if one plans to teach engineers how to apply the method.

CONCLUSION

Achieving the quality standards of the 1990s requires a preventative philosophy, not a reactive one. The goal is to apply technical expertise at the earliest stages of design in the form of SPC process capability studies, process optimization, and parameter design. Statistical process control involves everyone in process improvement by providing objective, workable data. It allows continuous improvement instead of merely aiming for all parts to be within a tolerance band.

Process capability studies, control charts, and loss function analysis are but a few of the tools available in the effort to reduce variation. When used in tandem with an implementation plan, these tools can help reduce variability, which can lead directly to producing highly reliable systems while reducing development time and costs.

Japanese business leaders recognized the value of a statistical approach beginning in 1950, and they made statistical control a cornerstone of their economic rebirth. In fact, if there is one single "secret" to the post-war Japanese success, it is the relentless daily pursuit of productivity and quality improvement using statistical methods.

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