Chapter 4

STEPS IN ROBUST DESIGN

As explained in Chapter 2, optimizing a product or process design means determining the best architecture, levels of control factors, and tolerances. Robust Design is a methodology for finding the optimum settings of the control factors to make the product or process insensitive to noise factors. It involves eight steps that can be grouped into the three major categories of planning experiments, conducting them, and analyzing and verifying the results.

- **Planning the experiment**

  1) Identify the main function, side effects, and failure modes.

  2) Identify noise factors and the testing conditions for evaluating the quality loss.

  3) Identify the quality characteristic to be observed and the objective function to be optimized.

  4) Identify the control factors and their alternate levels.

  5) Design the matrix experiment and define the data analysis procedure.

- **Performing the experiment**

  6) Conduct the matrix experiment.

- **Analyzing and verifying the experiment results**

  7) Analyze the data, determine optimum levels for the control factors, and predict performance under these levels.

  8) Conduct the verification (also called *confirmation*) experiment and plan future actions.

These eight steps make up a Robust Design cycle. We will illustrate them in this chapter by using a case study of improving a polysilicon deposition process. The case study was conducted by Peter Hey in 1984 as a class project for the first offering of the 3-day Robust Design course developed by the author, Madhav Phadke, and Chris Sherrerd, Paul Sherry, and Rajiv Keny of AT&T Bell Laboratories. Hey and Sherry jointly planned the experiment and analyzed the data. The experiment yielded a 4-fold reduction in the standard deviation of the thickness of the polysilicon layer and nearly two orders of magnitude reduction in surface defects, a major yield-limiting problem which was virtually eliminated. These results were achieved by studying the effects of six control factors by conducting experiments under 18 distinct combinations of the levels of these factors—a rather small investment for huge benefits in quality and yield.

This chapter consists of nine sections:

- Sections 4.1 through 4.8 describes in detail the polysilicon deposition process case study in terms of the eight steps that form a Robust Design cycle.
- Section 4.9 summarizes the important points of this chapter.

4.1 THE POLYSILICON DEPOSITION PROCESS AND ITS MAIN FUNCTION

Manufacturing very large scale intergrated (VLSI) circuits involves about 150 major steps. Deposition of polysilicon comes after about half of the steps are complete, and, as a result, the silicon wafers (thin disks of silicon) used in the process have a significant amount of value added by the time they reach this step. The polysilicon layer is very important for defining the gate electrodes for the transistors. There are over 250,000 transistors in a square centimeter chip area for the 1.75 micron (micrometer ≡ micron) design rules used in the case study.

A hot-wall, reduced-pressure reactor (see Figure 4.1) is used to deposit polysilicon on a wafer. The reactor consists of a quartz tube which is heated by a 3-zone furnace. Silane and nitrogen gases are introduced at one end and pumped out the other. The silane gas pyrolizes, and a polysilicon layer is deposited on top of the oxide layer on the wafers. The wafers are mounted on quartz carriers. Two carriers, each carrying 25 wafers, can be placed inside the reactor at a time so that polysilicon is deposited simultaneously on 50 wafers.

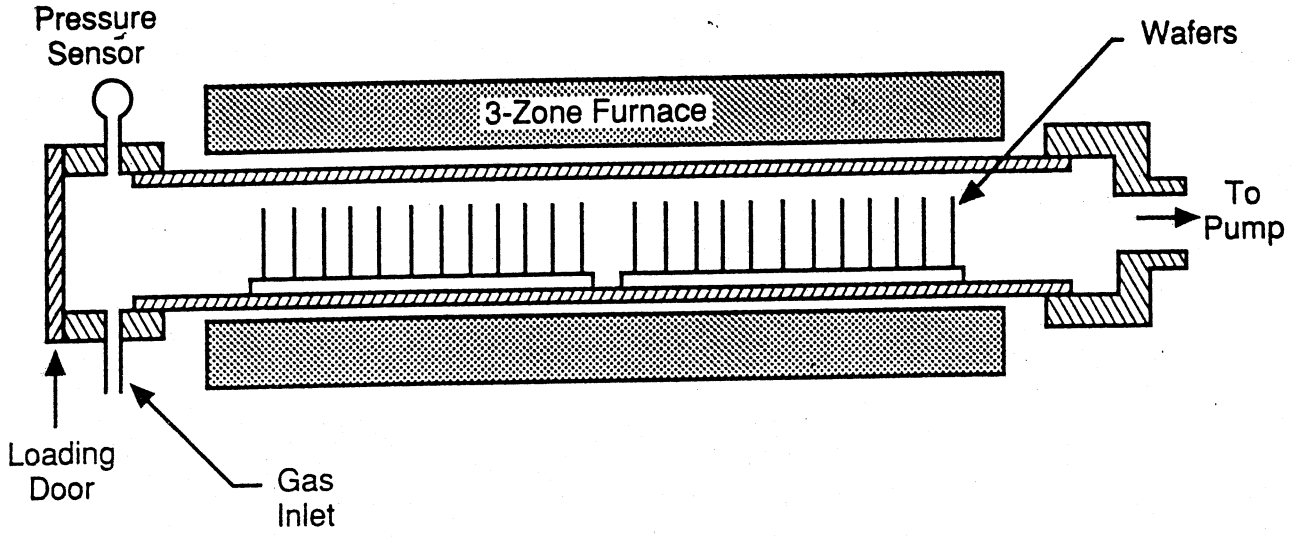


Figure 4.1 Schematic diagram of a reduced pressure reactor.

The function of the polysilicon deposition process is to deposit a uniform layer of a specified thickness. In the case study, the experimenters were interested in achieving 3600 angstrom(Å) thickness (1Å $= 10^{-10}$ meter). Figure 4.2 shows a cross section of the wafer after the deposition of the polysilicon layer.

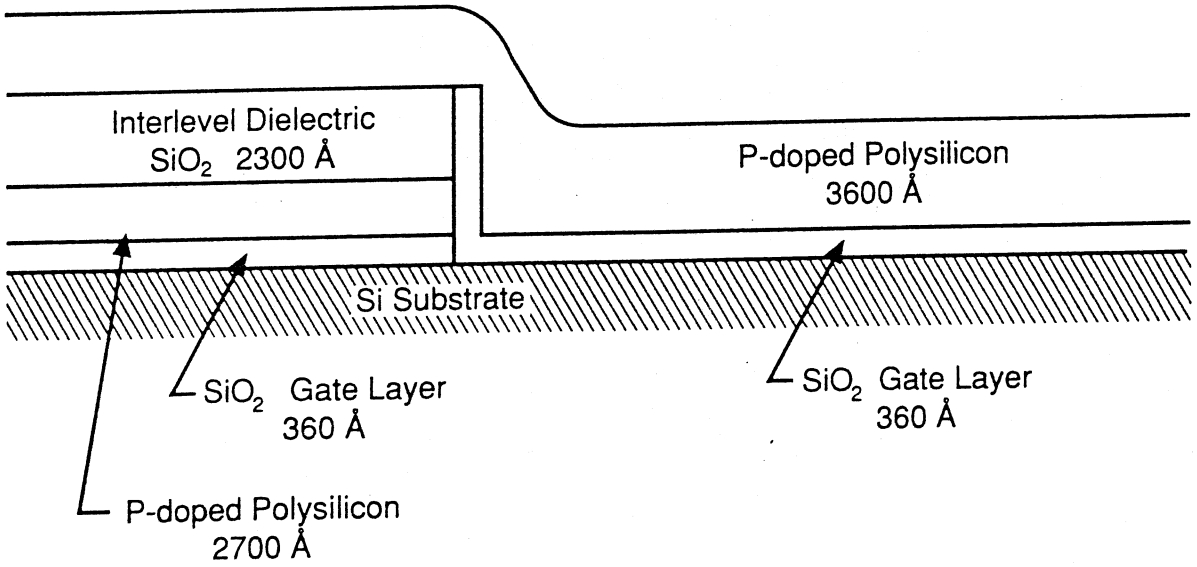


Figure 4.2 Cross section of a wafer showing polysilicon layer.

At the start of the study, two main problems occurred during the deposition process: (1) too many surface defects (see Figure 4.3) were encountered, and (2) too large

a thickness variation existed within wafers and among wafers. In a subsequent VLSI manufacturing step, the polysilicon layer is patterned by an etching process to form lines of appropriate width and length. Presence of surface defects causes these lines to have variable width, which degrades the performance of the integrated circuits. The nonuniform thickness is detrimental to the etching process because it can lead to residual polysilicon in some areas and an etching away of the underlying oxide layer in other areas.

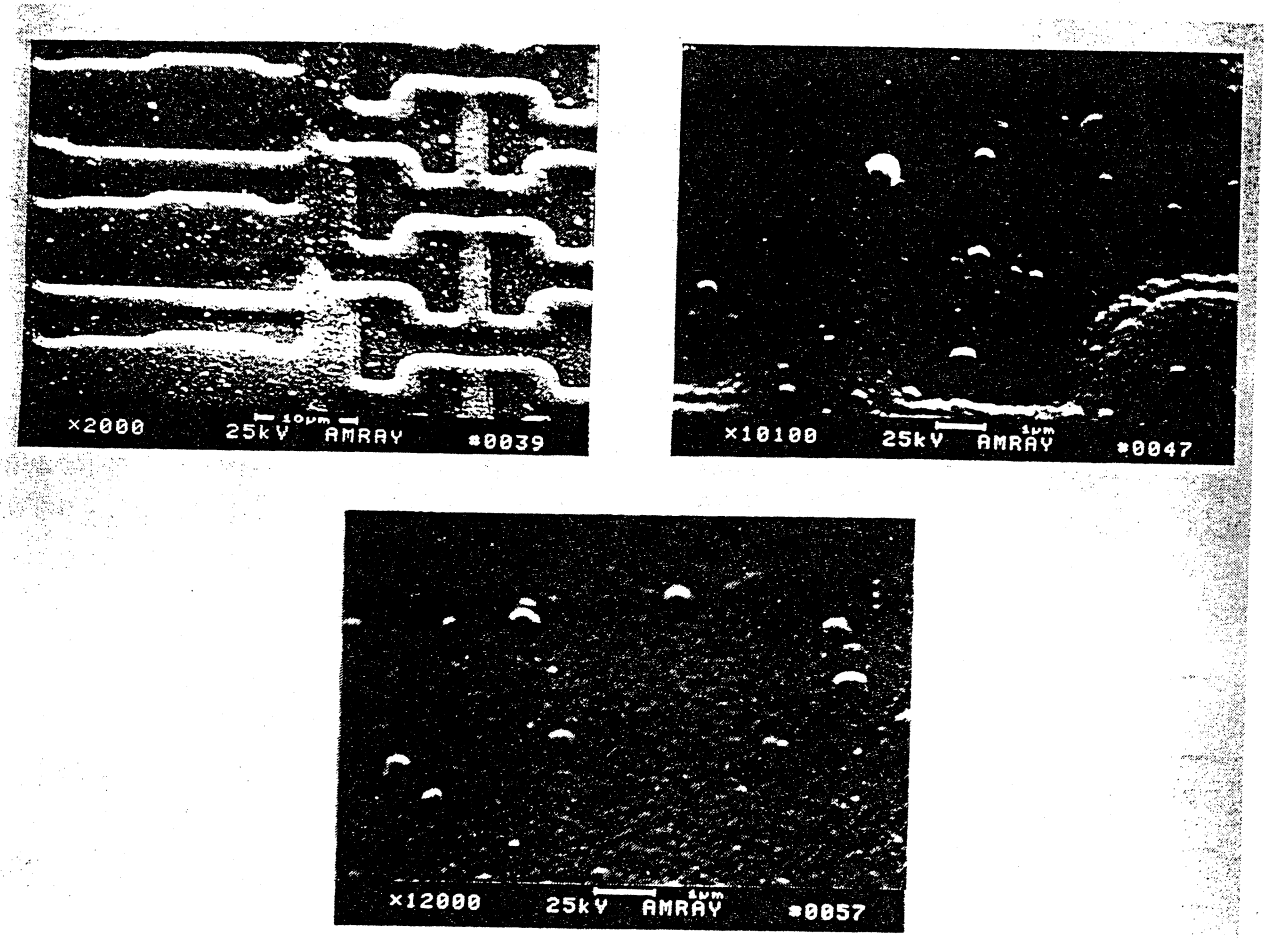


Figure 4.3 Photographs of polysilicon surface showing surface defects.

Prior to the case study, Hey noted that the surface-defect problem was crucial because a significant percentage of wafers were scrapped due to excessive defects. Also, he observed that controlling defect formation was particularly difficult due to its intermittent occurrence; for example, some batches of wafers (50 wafers make one batch) had approximately ten defects per unit area, while other batches had as many as 5,000 defects per unit area. Furthermore, no theoretical models existed to predict defect formation as a function of the various process parameters; therefore, experimentation was the only way to control the surface-defect problem. However, the

intermittency of the problem had rendered the traditional method of experimentation, where only one process parameter is changed at a time, virtually useless.

4.2 NOISE FACTORS AND TESTING CONDITIONS

To minimize sensitivity to noise factors, we must first be able to estimate the sensitivity in a consistent manner for any combination of the control factor levels. This is achieved through proper selection of testing conditions.

In a Robust Design project, we identify all noise factors (factors whose levels cannot be controlled during manufacturing, which are difficult to control, or expensive to control), and then select a few testing conditions that capture the effect of the more important noise factors. Simulating the effects of all noise factors is impractical because the experimenter may not know all the noise sources and because total simulation would require too many testing conditions and be costly. Although it is not necessary to include the effect of all noise factors, the experimenter should list as many of them as possible and, then, use engineering judgment to decide which are more important and what testing conditions are appropriate to capture their effects.

Various noise factors exist in the deposition process. The nonuniform thickness and the surface defects of the polysilicon layer are caused by the variations in the parameters involved in the chemical reactions associated with the deposition process. First, the gases are introduced at one end of the reactor (see Figure 4.1). As they travel to the other end, the silane gas decomposes into polysilicon, which is deposited on the wafers, and into hydrogen. This activity causes a *concentration gradient* along the length of the reactor. Further, the *flow pattern* (direction and speed) of the gases need not be the same as they travel from one end of the tube to the other. The flow pattern could also vary from one part of a wafer to other parts of the same wafer. Another important noise factor is the *temperature* variation along the length and cross section of the tube. There are, of course, other sources of variation or noise factors, such as *topography of the wafer surface* before polysilicon deposition, variation in *pumping speed*, and variation in *gas supply*.

For the case study of the polysilicon deposition process, Hey and Sherry decided to process one batch of 50 wafers to evaluate the quality associated with each combination of control factor settings suggested by the orthogonal array experiment. Of these 50 wafers, only 3 were test wafers, while the remaining 47 were dummy wafers, which provided the needed "full load" effect while saving the cost of expensive test wafers. To capture the variation in reactant concentration, flow pattern variation, and temperature variation along the length of the tube, the test wafers were placed in positions 3, 23, and 48 along the tube. Furthermore, to capture the effect of noise variation across a wafer, the thickness and surface defects were measured at three points on each test wafer: top, middle, and bottom. Other noise factors were judged to be less important. To include their effect, the experimenters would have had to process multiple batches, thus making the experiments very expensive. Consequently, the other noise factors were ignored.

The testing conditions for this case study are rather simple: observe thickness and surface defects at three positions of three wafers, which are placed in specific positions along the length of the reactor. Sometimes orthogonal arrays (called *noise orthogonal arrays*) are used to determine the testing conditions that capture the effect of many noise factors. In some other situations, the technique of *compound noise factor* is used. These two techniques of constructing testing conditions are described in Chapter 8.

4.3 QUALITY CHARACTERISTICS AND OBJECTIVE FUNCTIONS

It is often tempting to observe the percentage of units that meet the specification and use that percentage directly as an objective function to be optimized. But, such temptation should be meticulously avoided. Besides being a poor measure of quality loss, using percentage of good (or bad) wafers as an objective function leads to orders of magnitude reduction in efficiency of experimentation. First, to observe accurately the percentage of "good" wafers, we need a large number (much larger than three) of test wafers for each combination of control factor settings. Secondly, when the percentage of good wafers is used as an objective function, the interactions among control factors often become dominant; consequently, additive models cannot be used as adequate approximations. The appropriate quality characteristics to be measured for the polysilicon deposition process in the case study were the polysilicon thickness and the surface defect count. The specifications were that the thickness should be within ± 8 percent of the target thickness and that the surface defect count should not exceed 10 per square centimeter.

As stated in Section 4.2, nine measurements (3 wafers × 3 measurements per wafer) of thickness and surface defects were taken for each combination of control factor settings in the matrix experiment. The ideal value for surface defects is zero—the smaller the number of surface defects per cm^2, the better the wafer. So, by adopting the quadratic loss function, we see that the objective function to be maximized is

$$\eta = -10 \log_{10} (\text{mean square surface defects})$$

$$= -10 \log_{10} \left\{ \frac{1}{9} \sum_{i=1}^{3} \sum_{j=1}^{3} y_{ij}^2 \right\} \tag{4.1}$$

where y_{ij} is the observed surface defect count at position j on test wafer i. Note that j=1, 2, and 3 stand for top, center, and bottom positions, respectively, on a test wafer. And i=1, 2, and 3 refer to position numbers 3, 23, and 48, respectively, along the length of the tube. Maximizing η leads to minimization of the quality loss due to surface defects.

The target value in the study for the thickness of the polysilicon layer was $\tau_0 = 3600$ Å. Let τ_{ij} be the observed thickness at position j on test wafer i. The mean and variance of the thickness are given by

$$\mu = \frac{1}{9} \sum_{i=1}^{3} \sum_{j=1}^{3} \tau_{ij} \tag{4.2}$$

$$\sigma^2 = \frac{1}{8} \sum_{i=1}^{3} \sum_{j=1}^{3} (\tau_{ij} - \mu)^2. \tag{4.3}$$

The goal in optimization for thickness is to minimize variance while keeping the mean on target. This is a constrained optimization problem, which can be very difficult, especially when many control factors exist. However, as Chapter 5 shows, when a *scaling factor* (a factor that increases the thickness proportionally at all points on the wafers) exists, the problem can be simplified greatly.

In the case study, the deposition time was a clear scaling factor—that is, for every surface area where polysilicon was deposited, (thickness) = (deposition rate) × (deposition time). The deposition rate may vary from one wafer to the next, or from one position on a wafer to another position, due to the various noise factors cited in the previous section. However, the thickness at any point is proportional to the deposition time.

Thus, the constrained optimization problem in the case study can be solved in two steps as follows:

1. Maximize the Signal-to-noise (S/N) ratio, η',

$$\eta' = 10 \log_{10} \frac{\mu^2}{\sigma^2}. \tag{4.4}$$

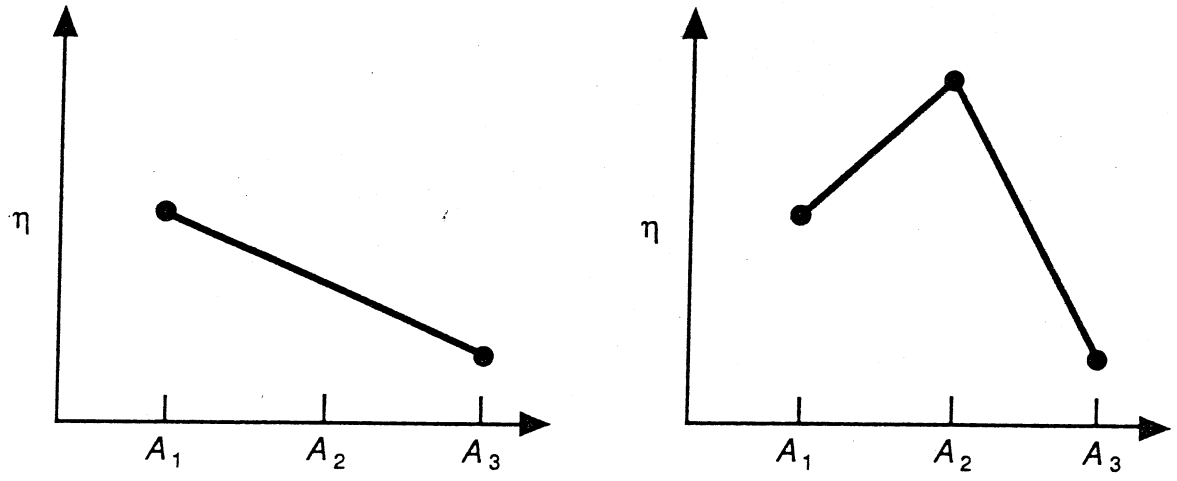
2. Adjust the deposition time so that mean thickness is on target.

In summary, the two quality characteristics to be measured were the surface defects and the thickness. The corresponding objective functions to be maximized were η and η' defined by Equations (4.1) and (4.4), respectively. (Note that S/N ratio is a general term used for measuring sensitivity to noise factors. It takes a different form depending on the type of quality characteristic, as discussed in detail in Chapter 5. Both η and η' are different types of S/N ratios.)

The economics of a manufacturing process is determined by the throughput as well as by the quality of the products produced. Therefore, along with the quality characteristics, a throughput characteristic also must be studied. Thus, in the case study, the experimenters also observed the deposition rate, r, measured in angstroms of thickness growth per minute.

4.4 CONTROL FACTORS AND THEIR LEVELS

Processes, such as polysilicon deposition, typically have a large number of control factors (factors that can be freely specified by the process designer). The more complex a process, the more control factors it has and vice versa. Typically, we choose six to eight control factors at a time to optimize a process. For each factor we generally select two or three levels (or settings) and take the levels sufficiently far apart so that a wide region can be covered by the three levels. Commonly, one of these levels is taken to be the initial operating condition. Note that we are interested in the nonlinearity, so taking the levels of control factors too close together is not very fruitful. If we take only two levels, curvature effects would be missed, whereas such effects can be identified by selecting three levels for a factor (see Figure 4.4). Furthermore, by selecting three levels, we can simultaneously explore the region on either side of the initial operating condition. Hence, we prefer three levels.



(a) With two points we can only fit a straight line.

(b) With three points we can identify curvature effects and, hence, peaks.

Figure 4.4 Linear and curvature effects of a factor.

In the case study, six control factors were selected for optimization. These factors and their alternate levels are listed in Table 4.1. The deposition temperature (A) is the steady state temperature at which the deposition takes place. When the wafers are placed in the reactor, they first have to be heated from room temperature to the deposition temperature and then held at that temperature. The deposition pressure (B) is the constant pressure maintained inside the reactor through appropriate pump speed and butterfly adjustment. The nitrogen flow (C) and the silane flow (D) are adjusted using the corresponding flow meters on gas tanks. Settling time (E) is the time between placing the wafer carriers in the reactors and the time at which gases flow. The settling time is important for establishing thermal and pressure equilibrium inside the

reactor before the reaction is allowed to start. Cleaning method (F) refers to cleaning the wafers prior to the deposition step. Before undertaking the case study experiment, the practice was to perform no cleaning. The alternate two cleaning methods the experimenters wanted to study were CM_2, performed inside the reactor, and CM_3, performed outside the reactor.

TABLE 4.1 CONTROL FACTORS AND THEIR LEVELS

Factor	Levels*		
	1	2	3
A. Deposition temperature (°C)	T_0-25	$\underline{T_0}$	T_0+25
B. Deposition pressure (mtorr)	P_0-200	$\underline{P_0}$	P_0+200
C. Nitrogen flow (sccm)	$\underline{N_0}$	N_0-150	N_0-75
D. Silane flow (sccm)	S_0-100	S_0-50	$\underline{S_0}$
E. Settling time (min)	$\underline{t_0}$	t_0+8	t_0+16
F. Cleaning method	$\underline{None}$	CM_2	CM_3

* Starting levels are identified by underscore.

While deciding on the levels of control factors, a frequent tendency is to choose the levels relatively close to the starting levels. This is due to the experimenter's concern that a large number of bad products may be produced during the matrix experiment. But, producing bad products during the experiment stage may, in fact, be beneficial because it tells us which region of control factor levels should be avoided. Also, by choosing levels that are wide apart, we increase the chance of capturing the nonlinearity of the relationship between the control factors and the noise factors, and, thus, finding the levels of control factors that minimize sensitivity to noise. Further, when the levels are wide apart, the factor effects are large when compared to the experimental errors. As a result, the factor effects can be identified without too many repetitions.

Thus, it is important to resist the tendency to choose control factor levels that are rather close. Of course, during subsequent refinement experiments, levels closer to each other could be chosen. In the polysilicon deposition case study, the ratio of the largest to the smallest levels of factors B, C, D, and, E was between three and five which represents a wide variation. Temperature variation from (T_0-25) °C to (T_0+25) °C also represents a wide range in terms of the known impact on the deposition rate.

The initial settings of the six control factors are indicated by an *underscore* in Table 4.1. The objective of this project was to determine the optimum level for each factor so that η and η' are improved, while ensuring simultaneously that the deposition rate, r, remained as high as possible. Note that the six control factors and their selected settings define the experimental region over which process optimization was done.

4.5 MATRIX EXPERIMENT AND DATA ANALYSIS PLAN

An efficient way to study the effect of several control factors simultaneously is to plan matrix experiments using orthogonal arrays. As pointed out in Chapter 3, orthogonal arrays offer many benefits. First, the conclusions arrived at from such experiments are valid over the entire experimental region spanned by the control factors and their settings. Second, there is a large saving in the experimental effort. Third, the data analysis is very easy. Finally, it can detect departure from the additive model.

An orthogonal array for a particular Robust Design project can be constructed from the knowledge of the number of control factors, their levels, and the desire to study specific interactions. While constructing the orthogonal array, we also take into account the difficulties in changing the levels of control factors, other physical limitations in conducting experiments, and the availability of resources. In the polysilicon deposition case study, there were six factors, each at three levels. The experimenters found no particular reason to study specific interactions and no unusual difficulty in changing the levels of any factor. The available resources for conducting the experiments were such that about 20 batches could be processed and appropriate measurements made. Using the standard methods of constructing orthogonal arrays, which are described in Chapter 7, the standard array L_{18} was selected for this matrix experiment.

The L_{18} orthogonal array is given in Table 4.2. It has eight columns and eighteen rows. The first column is a 2-level column—that is, it has only two distinct entries, namely 1 or 2. All the chosen six control factors have three levels. So, column 1 was kept empty or unassigned. From the remaining seven 3-level columns, column 7 was arbitrarily designated as an empty column, and factors A through F were assigned, respectively, to columns 2 through 6 and 8. (Note that keeping one or more columns empty does not alter the orthogonality property of the array. Thus, the matrix formed by columns 2 through 6 and 8 is still an orthogonal array. But, if one or more rows are dropped, the orthogonality is destroyed.) The reader can verify the orthogonality by checking that for every pair of columns all combinations of levels occur, and they occur an equal number of times.

The 18 rows of the L_{18} array represent the 18 experiments to be conducted. Thus, experiment 1 is to be conducted at level 1 for each of the six control factors. These levels can be read from Table 4.1. However, to make it convenient for the experimenter and to prevent translation errors, the entire matrix of Table 4.2 should be

translated using the level definitions in Table 4.1 to create the experimenter's log sheet shown in Table 4.3.

TABLE 4.2 L_{18} ORTHOGONAL ARRAY AND FACTOR ASSIGNMENT

Expt. No.	Column Numbers and Factor Assignment*							
	1 e	2 A	3 B	4 C	5 D	6 E	7 e	8 F
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

* Empty columns are identified by e.

TABLE 4.3 EXPERIMENTER'S LOG

Expt. No.	Temperature	Pressure	Nitrogen	Silane	Settling Time	Cleaning Method
1	T_0-25	P_0-200	N_0	S_0-100	t_0	*None*
2	T_0-25	P_0	N_0-150	S_0-50	t_0+8	CM_2
3	T_0-25	P_0+200	N_0-75	S_0	t_0+16	CM_3
4	T_0	P_0-200	N_0	S_0-50	t_0+8	CM_3
5	T_0	P_0	N_0-150	S_0	t_0+16	*None*
6	T_0	P_0+200	N_0-75	S_0-100	t_0	CM_2
7	T_0+25	P_0-200	N_0-150	S_0-100	t_0+16	CM_3
8	T_0+25	P_0	N_0-75	S_0-50	t_0	*None*
9	T_0+25	P_0+200	N_0	S_0	t_0+8	CM_2
10	T_0-25	P_0-200	N_0-75	S_0	t_0+8	*None*
11	T_0-25	P_0	N_0	S_0-100	t_0+16	CM_2
12	T_0-25	P_0+200	N_0-150	S_0-50	t_0	CM_3
13	T_0	P_0-200	N_0-150	S_0	t_0	CM_2
14	T_0	P_0	N_0-75	S_0-100	t_0+8	CM_3
15	T_0	P_0+200	N_0	S_0-50	t_0+16	*None*
16	T_0+25	P_0-200	N_0-75	S_0-50	t_0+16	CM_2
17	T_0+25	P_0	N_0	S_0	t_0	CM_3
18	T_0+25	P_0+200	N_0-150	S_0-100	t_0+8	*None*

Now we combine the experimenter's log sheet with the testing conditions described in Section 4.2 to create the following experimental procedure:

1. Conduct 18 experiments as specified by the 18 rows of Table 4.3.
2. For each experiment, process one batch, consisting of 47 dummy wafers and three test wafers. The test wafers should be placed in positions 3, 23, and 48.

3. For each experiment, compute to your best ability the deposition time needed to achieve the target thickness of 3600Å. Note that in the experiment the actual thickness may turn out to be much different from 3600Å. However, such data are perfectly useful for analysis. Thus, a particular experiment *need not* be redone by adjusting the deposition time to obtain 3600Å thickness.

4. For each experiment, measure the surface defects and thickness at three specific points (top, center, and bottom) on each test wafer. Follow standard laboratory practice to prepare data sheets with space for every observation to be recorded.

4.6 CONDUCTING THE MATRIX EXPERIMENT

From Table 4.3 it is apparent that, from one experiment to the next, levels of several control factors must be changed. This poses a considerable amount of difficulty to the experimenter. Meticulousness in correctly setting the levels of the various control factors is critical to the success of a Robust Design project. Let us clarify what we mean by meticulousness. Going from experiment 3 to experiment 4 we must change temperature from $(T_0 - 25)$ °C to T_0 °C, pressure from $(P_0 + 200)$ mtorr to $(P_0 - 200)$ mtorr, and so on. By meticulousness we mean ensuring that the temperature, pressure, and other dials are set to their proper levels. Failure to set the level of a factor correctly could destroy the valuable property of orthogonality. Consequently, conclusions from the experiment could be erroneous. However, if an inherent error in the equipment leads to an actual temperature of $(T_0 - 1)$ °C or $(T_0 + 2)$ °C when the dial is set at T_0 °C, we should not bother to correct for such variations. Why? Because unless we plan to change the equipment, such variations constitute noise and will continue to be present during manufacturing. If our conclusions from the matrix experiment are to be valid in actual manufacturing, our results must not be sensitive to such inherent variations. By keeping these variations out of our experiments, we lose the ability to test for robustness against such variations. The matrix experiment, coupled with the verification experiment, has a built-in check for sensitivity to such inherent variations.

A difficulty in conducting matrix experiments is their radical difference from the current practice of conducting product or process design experiments. One common practice is to guess, using engineering judgment, the improved settings of the control factors and then conduct a paired comparison with the starting conditions. The guess-and-test cycle is repeated until some minimum improvement is obtained, the deadline is reached, or the budget is exhausted. This practice relies heavily on luck, and it is inefficient and time-consuming.

Another common practice is to optimize systematically one control factor at a time. Suppose we wish to determine the effect of the three temperature settings while keeping the settings of the other control factors fixed at their starting levels. To reduce the effect of experimental error, we must process several batches at each temperature

setting. Suppose six batches are processed at each temperature setting. (Note that in the L_{18} array the replication number is six; that is, there are six experiments for each factor level.) Then, we would need 18 batches to evaluate the effect of three temperature settings. For the other factors, we need to experiment with the two alternate levels, so that we need to process 12 batches each. Thus, for the six factors, we would need to process $18 + 5 \times 12 = 78$ batches. This is a large number compared to the 18 batches needed for the matrix experiment. Further, if there are strong interactions among the control factors, this method of experimentation cannot detect them.

The matrix experiment, though somewhat tedious to conduct, is highly efficient—that is, when compared to the practices above, we can generate more dependable information about more control factors with the same experimental effort. Also, this method of experimentation allows for the detection of the interactions among the control factors, when they are present, through the verification experiment.

In practice, many design improvement experiments, where only one factor is studied at a time, get terminated after studying only a few control factors because both the R&D budget and the experimenter's patience run out. As a result, the quality improvement turns out to be only partial, and the product cost remains somewhat high. This danger is reduced greatly when we conduct matrix experiments using orthogonal arrays.

In the polysilicon deposition case study, the 18 experiments were conducted according to the experimenter's log given in Table 4.3. It took only nine days (2 experiments per day) to conduct them. The observed data on surface defects are listed in Table 4.4(a), and the thickness and deposition rate data are shown in Table 4.4(b). The surface defects were measured by placing the specimen under an optical microscope and counting the defects in a field of 0.2 cm^2. When the count was high, the field area was divided into smaller areas, defects in one area were counted, and the count was then multiplied by an appropriate number to determine the defect count per unit area (0.2 cm^2). The thickness was measured by an optical interferometer. The deposition rate was computed by dividing the average thickness by the deposition time.

4.7 DATA ANALYSIS

The first step in data analysis is to summarize the data for each experiment. For the case study, these calculations are illustrated next.

For experiment number 1, the S/N ratio for the surface defects, given by Equation (4.1), was computed as follows:

$$\eta = -10 \log_{10} \left[\frac{1}{9} \sum_{i=1}^{3} \sum_{j=1}^{3} y_{ij}^2 \right]$$

$$= -10 \log_{10} \left[\frac{(1^2+0^2+1^2)+(2^2+0^2+0^2)+(1^2+1^2+0^2)}{9} \right]$$

$$= -10 \log_{10} \left[\frac{8}{9} \right]$$

$$= 0.51.$$

From the thickness data, the mean, variance, and S/N ratio were calculated as follows by using Equations (4.2), (4.3) and (4.4):

See Eq. (4.2) $\mu = \frac{1}{9} \sum_{i=1}^{3} \sum_{j=1}^{3} \tau_{ij}$

$$= \frac{1}{9} \left[(2029+1975+1961) + (1975+1934+1907) + (1952+1941+1949) \right]$$

$$= 1958.1 \text{ Å} .$$

See Eq. (4.3) $\sigma^2 = \frac{1}{8} \sum_{i=1}^{3} \sum_{j=1}^{3} (\tau_{ij} - \mu)^2$

$$= \frac{1}{8} \left[(2029-1958.1)^2 + \cdots + (1949-1958.1)^2 \right]$$

$$= 1151.36 \text{ (Å)}^2.$$

$$\eta' = 10 \log_{10} \frac{\mu^2}{\sigma^2}$$

$$= 10 \log_{10} \frac{1958.1^2}{1151.36}$$

$$= 35.22 \text{ dB}.$$

TABLE 4.4(a) SURFACE DEFECT DATA (DEFECTS/UNIT AREA)

Expt. No.	Test Wafer 1			Test Wafer 2			Test Wafer 3		
	Top	Center	Bottom	Top	Center	Bottom	Top	Center	Bottom
1	1	0	1	2	0	0	1	1	0
2	1	2	8	180	5	0	126	3	1
3	3	35	106	360	38	135	315	50	180
4	6	15	6	17	20	16	15	40	18
5	1720	1980	2000	487	810	400	2020	360	13
6	135	360	1620	2430	207	2	2500	270	35
7	360	810	1215	1620	117	30	1800	720	315
8	270	2730	5000	360	1	2	9999	225	1
9	5000	1000	1000	3000	1000	1000	3000	2800	2000
10	3	0	0	3	0	0	1	0	1
11	1	0	1	5	0	0	1	0	1
12	3	1620	90	216	5	4	270	8	3
13	1	25	270	810	16	1	225	3	0
14	3	21	162	90	6	1	63	15	39
15	450	1200	1800	2530	2080	2080	1890	180	25
16	5	6	40	54	0	8	14	1	1
17	1200	3500	3500	1000	3	1	9999	600	8
18	8000	2500	3500	5000	1000	1000	5000	2000	2000

TABLE 4.4(b) THICKNESS AND DEPOSITION RATE DATA

Expt. No.	Thickness (Å)									Deposition Rate (Å/min)
	Test Wafer 1			Test Wafer 2			Test Wafer 3			
	Top	Center	Bottom	Top	Center	Bottom	Top	Center	Bottom	
1	2029	1975	1961	1975	1934	1907	1952	1941	1949	14.5
2	5375	5191	5242	5201	5254	5309	5323	5307	5091	36.6
3	5989	5894	5874	6152	5910	5886	6077	5943	5962	41.4
4	2118	2109	2099	2140	2125	2108	2149	2130	2111	36.1
5	4102	4152	4174	4556	4504	4560	5031	5040	5032	73.0
6	3022	2932	2913	2833	2837	2828	2934	2875	2841	49.5
7	3030	3042	3028	3486	3333	3389	3709	3671	3687	76.6
8	4707	4472	4336	4407	4156	4094	5073	4898	4599	105.4
9	3859	3822	3850	3871	3922	3904	4110	4067	4110	115.0
10	3227	3205	3242	3468	3450	3420	3599	3591	3535	24.8
11	2521	2499	2499	2576	2537	2512	2551	2552	2570	20.0
12	5921	5766	5844	5780	5695	5814	5691	5777	5743	39.0
13	2792	2752	2716	2684	2635	2606	2765	2786	2773	53.1
14	2863	2835	2859	2829	2864	2839	2891	2844	2841	45.7
15	3218	3149	3124	3261	3205	3223	3241	3189	3197	54.8
16	3020	3008	3016	3072	3151	3139	3235	3162	3140	76.8
17	4277	4150	3992	3888	3681	3572	4593	4298	4219	105.3
18	3125	3119	3127	3567	3563	3520	4120	4088	4138	91.4

The deposition rate in the decibel scale for experiment 1 is given by

$$\eta'' = 10 \log_{10} r^2 = 20 \log_{10} r$$

$$= 20 \log_{10}(14.5)$$

$$= 23.23 \text{ dBam}$$

where dBam stands for decibel Å /min.

The data summary for all 18 experiments was computed in a similar fashion and the results are tabulated in Table 4.5.

Observe that the mean thickness for the 18 experiments ranges from 1958 Å to 5965 Å . But we are least concerned about this variation in the thickness because the average thickness can be adjusted easily by changing the deposition time. During a Robust Design project, what we are most interested in is the S/N ratio, which in this case is a measure of variation in thickness as a proportion of the mean thickness. Hence, no further analysis on the mean thickness was done in the case study, but the mean thickness, of course, was used in computing the deposition rate, which was of interest.

After the data for each experiment are summarized, the next step in data analysis is to estimate the effect of each control factor on each of the three characteristics of interest and to perform analysis of variance (ANOVA) as described in Chapter 3.

The factor effects for surface defects (η), thickness (η'), and deposition rate (η''), and the respective ANOVA are given in Tables 4.6, 4.7, and 4.8, respectively. A summary of the factor effects is tabulated in Table 4.9, and the factor effects are displayed graphically in Figure 4.5, which makes it easy to visualize the relative effects of the various factors on all three characteristics.

To assist the interpretation of the factor effects plotted in Figure 4.5, we note the following relationship between the decibel scale and the natural scale for the three characteristics:

- An increase in η by 6 dB is equivalent to a reduction in the root mean square surface defects by a factor of 2. An increase in η by 20 dB is equivalent to a reduction in the root mean square surface defects by a factor of 10.
- The above statements are valid if we substitute η' or η'' for η, and standard deviation of thickness or deposition rate for root mean square surface defects.

The task of determining the best setting for each control factor can become complicated when there are multiple characteristics to be optimized. This is because different levels of the same factor could be optimum for different characteristics. The quality loss function could be used to make the necessary trade-offs when different characteristics suggest different optimum levels. For the polysilicon deposition case

TABLE 4.5 DATA SUMMARY BY EXPERIMENT

Expt. No.	Experiment Condition Matrix* e A B C D E e F	Surface Defects η (dB)	Thickness μ (Å)	Thickness η' (dB)	Deposition Rate η'' (dBam)
1	1 1 1 1 1 1 1 1	0.51	1958	35.22	23.23
2	1 1 2 2 2 2 2 2	−37.30	5255	35.76	31.27
3	1 1 3 3 3 3 3 3	−45.17	5965	36.02	32.34
4	1 2 1 1 2 2 3 3	−25.76	2121	42.25	31.15
5	1 2 2 2 3 3 1 1	−62.54	4572	21.43	37.27
6	1 2 3 3 1 1 2 2	−62.23	2891	32.91	33.89
7	1 3 1 2 1 3 2 3	−59.88	3375	21.39	37.68
8	1 3 2 3 2 1 3 1	−71.69	4527	22.84	40.46
9	1 3 3 1 3 2 1 2	−68.15	3946	30.60	41.21
10	2 1 1 3 3 2 2 1	−3.47	3415	26.85	27.89
11	2 1 2 1 1 3 3 2	−5.08	2535	38.80	26.02
12	2 1 3 2 2 1 1 3	−54.85	5781	38.06	31.82
13	2 2 1 2 3 1 3 2	−49.38	2723	32.07	34.50
14	2 2 2 3 1 2 1 3	−36.54	2852	43.34	33.20
15	2 2 3 1 2 3 2 1	−64.18	3201	37.44	34.76
16	2 3 1 3 2 3 1 2	−27.31	3105	31.86	37.71
17	2 3 2 1 3 1 2 3	−71.51	4074	22.01	40.45
18	2 3 3 2 1 2 3 1	−72.00	3596	18.42	39.22

* Empty column is denoted by e.

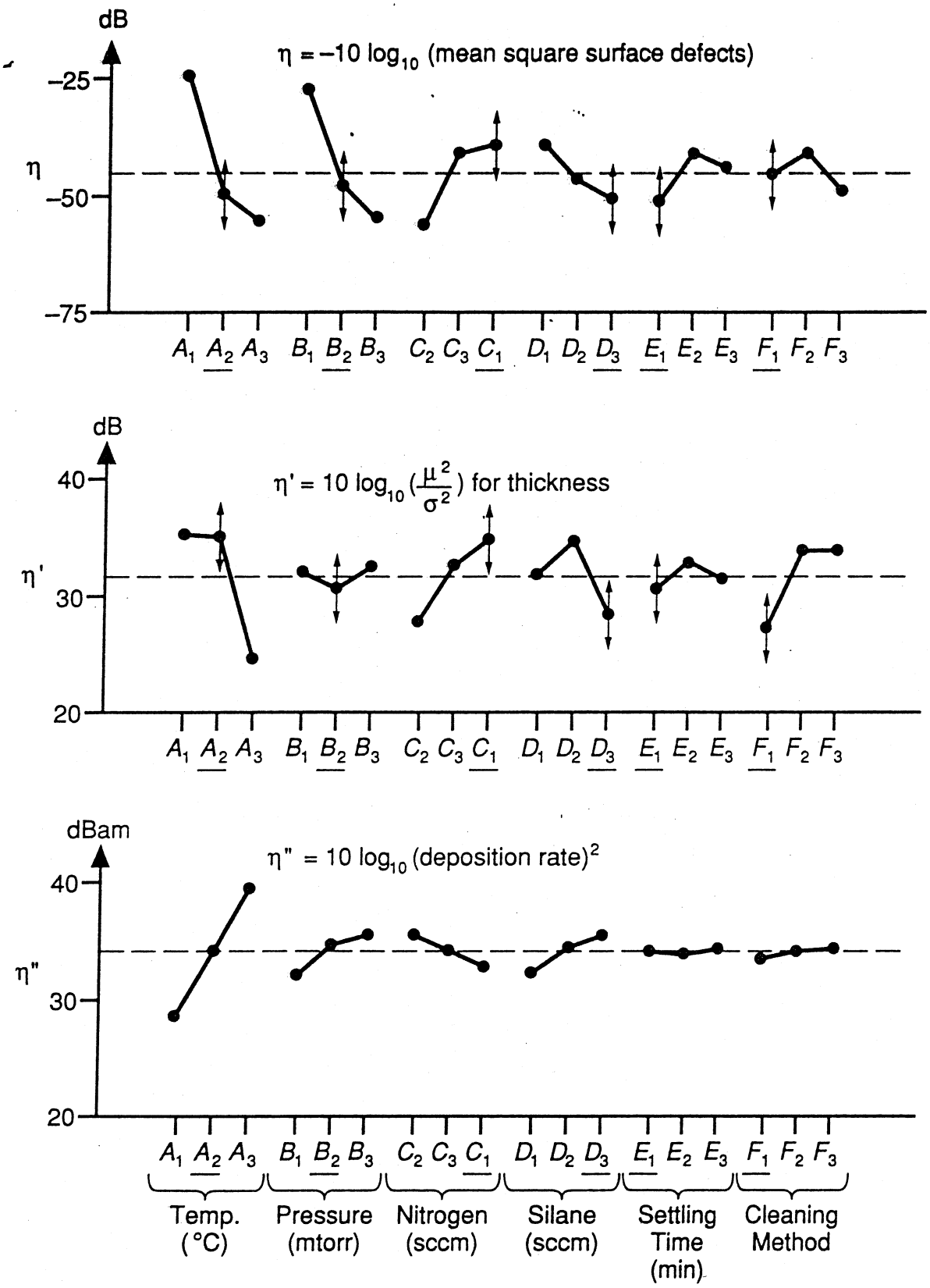


Figure 4.5 Plots of factor effects. Underline indicates starting level. Two-standard-deviation confidence limits are also shown for the starting level. Estimated confidence limits for η'' are too small to show.

study, we can make the following observations about the optimum setting from Figure 4.5 and Table 4.9:

- Deposition temperature (factor A) has the largest effect on all three characteristics. By reducing the temperature from the starting setting of T_0 °C to $T_0 - 25$ °C, η can be improved by $\{(-24.23) - (-50.10)\} \simeq 26$ dB. This is equivalent to a 20-fold reduction in root mean square surface defect count. The effect of this temperature change on thickness uniformity is only $(35.12 - 34.91) = 0.21$ dB, which is negligible. But the same temperature change would lead to a reduction in deposition rate by $(34.13 - 28.76) \simeq 5.4$ dB, which is approximately a 2-fold reduction in the deposition rate. Thus, temperature can dramatically reduce the surface defect problem, but it also would double the deposition time. Accordingly, there is a trade-off to be made between reducing the quality cost (including the scrap due to high surface defect count) and the number of wafers processed per day by the reactor.

- Deposition pressure (factor B) has the next largest effect on surface defect and deposition rate. Reducing the pressure from the starting level of P_0 mtorr to $(P_0 - 200)$ mtorr can improve η by about 20 dB (a 10-fold reduction in the root mean square surface defect count) at the expense of reducing the deposition rate by 2.75 dBam (37 percent reduction in deposition rate). The effect of pressure on thickness uniformity is very small.

- Nitrogen flow rate (factor C) has a moderate effect on all three characteristics. The starting setting of N_0 sccm gives the highest S/N ratios for surface defects and thickness uniformity. There is also a possibility of further improving these two S/N ratios by increasing the flow rate of this dilutant gas. This is an important fact to be remembered for future experiments. The effect of nitrogen flow rate on deposition rate is small compared to the effects of temperature and pressure.

- Silane flow rate (factor D) also has a moderate effect on all three characteristics. Thickness uniformity is the best when silane flow rate is set at $(S_0 - 50)$ sccm. This can also lead to a small reduction in surface defects and the deposition rate.

- Settling time (factor E) can be used to achieve about 10 dB improvement in surface defects by increasing the time from t_0 minutes to $(t_0 + 8)$ minutes. The data indicates that a further increase in the settling time to $(t_0 + 16)$ minutes could negate some of the reduction in surface defect count. However, this change is small compared to the standard deviation of the error; and it is not physically justifiable. Settling time has no effect on the deposition rate and the thickness uniformity.

- Cleaning method (factor F) has no effect on deposition rate and surface defects. But, by instituting some cleaning prior to deposition, the thickness uniformity can be improved by over 6.0 dB (a factor of 2 reduction in standard deviation of

thickness). Cleaning with CM_2 or CM_3 could give the same improvement in thickness uniformity. However, CM_2 cleaning can be performed inside the reactor, whereas CM_3 cleaning must be done outside the reactor. Thus, CM_2 cleaning is more convenient.

From these observations, the optimum settings of factors E and F are obvious, namely E_2 and F_2. However, for factors A through D, the direction in which the quality characteristics (surface defects and thickness uniformity) improve tend to reduce the deposition rate. Thus, a trade-off between quality loss and productivity must be made in choosing their optimum levels. In the case study, since surface defects were the key quality problem that caused significant scrap, the experimenters decided to take care of it by changing temperature from A_2 to A_1. As discussed earlier, this also meant a substantial reduction in deposition rate. Also, they decided to hold the other three factors at their starting levels, namely B_2, C_1, and D_3. The potential these factors held would

TABLE 4.6 ANALYSIS OF SURFACE DEFECTS DATA*

Factor	Average η by Factor Level (dB)			Degree of Freedom	Sum of Squares	Mean Square	F
	1	2	3				
A. Temperature	− 24.23	<u>−50.10</u>	− 61.76	2	4427	2214	27
B. Pressure	− 27.55	<u>−47.44</u>	− 61.10	2	3416	1708	21
C. Nitrogen	<u>−39.03</u>	− 55.99	− 41.07	2	1030	515	6.4
D. Silane	− 39.20	− 46.85	<u>−50.04</u>	2	372	186	2.3
E. Settling time	<u>−51.52</u>	− 40.54	− 44.03	2	378	189	2.3
F. Cleaning method	<u>−45.56</u>	− 41.58	− 48.95	2	164†	82	
Error				5	405†	81	
Total				17	10192		
(Error)				(7)	(569)	(81)	

* Overall mean η = −45.36 dB. Underscore indicates starting level.

† Indicates the sum of squares added together to form the pooled error sum of squares shown in parentheses.

have been used if the confirmation experiment indicated a need to improve the surface defect and thickness uniformity further. Thus, the optimum conditions chosen were: $A_1B_2C_1D_3E_2F_2$.

The next step in data analysis is to predict the anticipated improvements under the chosen optimum conditions. To do so, we first predict the S/N ratios for surface defects, thickness uniformity, and deposition rate using the additive model. These computations for the case study are displayed in Table 4.10. According to the table, an improvement in surface defects equal to $[-19.84-(-56.69)] = 36.85$ dB should be anticipated, which is equivalent to a reduction in the root mean square surface defect count by a factor of 69.6. The projected improvement in thickness uniformity is $36.79-29.95 = 6.84$ dB, which implies a reduction in standard deviation by a factor of 2.2. The corresponding change in deposition rate is $29.60-34.97 = -5.37$ dB, which amounts to a reduction in the deposition rate by a factor of 1.9.

TABLE 4.7 ANALYSIS OF THICKNESS DATA*

Factor	Average η' by Level (dB)			Degree of Freedom	Sum of Squares	Mean Square	F
	1	2	3				
A. Temperature	35.12	<u>34.91</u>	24.52	2	440	220	16
B. Pressure	31.61	<u>30.70</u>	32.24	2	7†	3.5	
C. Nitrogen	<u>34.39</u>	27.86	32.30	2	134	67	5.0
D. Silane	31.68	34.70	<u>28.17</u>	2	128	64	4.8
E. Settling time	<u>30.52</u>	32.87	31.16	2	18†	9	
F. Cleaning method	<u>27.04</u>	33.67	33.85	2	181	90.5	6.8
Error				5	96†	19.2	
Total				17	1004	59.1	
(Error)				(9)	(121)	(13.4)	

* Overall mean $\eta' = 31.52$ dB. Underscore indicates starting level.

† Indicates the sum of squares added together to form the pooled error sum of squares shown in parentheses.

TABLE 4.8 ANALYSIS OF DEPOSITION RATE DATA*

Factor	Average η'' by Factor Level (dBam)			Degree of Freedom	Sum of Squares	Mean Square	F
	1	2	3				
A. Temperature	28.76	34.13	39.46	2	343.1	171.5	553
B. Pressure	32.03	34.78	35.54	2	41.0	20.5	66
C. Nitrogen	32.81	35.29	34.25	2	18.7	9.4	30
D. Silane	32.21	34.53	35.61	2	36.3	18.1	58
E. Settling time	34.06	33.99	34.30	2	0.3†	0.2	
F. Cleaning method	33.81	34.10	34.44	2	1.2†	0.6	
Error				5	1.3†	0.26	
Total				17	441.9	25.9	
(Error)				(9)	(2.8)	(0.31)	

* Overall mean η'' = 34.12 dBam. Underscore indicates starting level.
† Indicates the sum of squares added together to form the pooled error sum of squares shown in parentheses.

4.8 VERIFICATION EXPERIMENT AND FUTURE PLAN

Conducting a verification experiment is a crucial final step of a Robust Design project. Its purpose is to verify that the optimum conditions suggested by the matrix experiment do indeed give the projected improvement. If the observed S/N ratios under the optimum conditions are close to their respective predictions, then we conclude that the additive model on which the matrix experiment was based is a good approximation of the reality. Then, we adopt the recommended optimum conditions for our process or product, as the case may be. However, if the observed S/N ratios under the optimum conditions differ drastically from their respective predictions, there is an evidence of failure of the additive model. There can be many reasons for the failure and, thus, there are many ways of dealing with it. The failure of the additive model generally indicates that choice of the objective function or the S/N ratio is inappropriate, the observed quality characteristic was chosen incorrectly, or the levels of the control factors were chosen inappropriately. The question of how to avoid serious additivity problems by properly choosing the quality characteristic, the S/N ratio, and the control factors and their levels is discussed in Chapter 6. Of course, another way to handle the

TABLE 4.9 SUMMARY OF FACTOR EFFECTS

Factor	Level	Surface Defects η (dB)	F	Thickness η' (dB)	F	Deposition Rate η'' (dBam)	F
A. Temperature (°C)	A_1: T_0−25	−24.23		35.12		28.76	
	A_2: T_0	−50.10	27	34.91	16	34.13	553
	A_3: T_0+25	−61.76		24.52		39.46	
B. Pressure (mtorr)	B_1: P_0−200	−27.55		31.61		32.03	
	B_2: P_0	−47.44	21	30.70	–	34.78	66
	B_3: P_0+200	−61.10		32.24		35.54	
C. Nitrogen (sccm)	C_1: N_0	−39.03		34.39		32.81	
	C_2: N_0−150	−55.99	6.4	27.86	5.0	35.29	30
	C_3: N_0−75	−41.07		32.30		34.25	
D. Silane (sccm)	D_1: S_0−100	−39.20		31.68		32.21	
	D_2: S_0−50	−46.85	2.3	34.70	4.8	34.53	58
	D_3: S_0	−50.04		28.17		35.61	
E. Settling time (min)	E_1: t_0	−51.52		30.52		34.06	
	E_2: t_0+8	−40.54	2.3	32.87	–	33.99	–
	E_3: t_0+16	−44.03		31.16		34.30	
F. Cleaning method	F_1: *None*	−45.56		27.04		33.81	
	F_2: CM_2	−41.58	–	33.67	6.8	34.10	–
	F_3: CM_3	−48.95		33.85		34.44	
Overall mean		−45.36		31.52		34.12	

additivity problem is to study a few key interactions among the control factors in future experiments. Construction of orthogonal arrays that permit the estimation of a few specific interactions, along with all main effects, is discussed in Chapter 7.

The verification experiment has two aspects: the first is that the predictions must agree under the laboratory conditions; the second aspect is that the predictions should be valid under actual manufacturing conditions for the process design and under actual field conditions for the product design. A judicious choice of both the noise factors to be included in the experiment and the testing conditions is essential for the predictions made through the laboratory experiment to be valid under both manufacturing and field conditions.

For the polysilicon deposition case study, four batches of 50 wafers containing 3 test wafers were processed under both the optimum condition and under the starting conditions. The results are tabulated in Table 4.11. It is clear that the data agree very well with the predictions about the improvement in the S/N ratios and the deposition rate. So, we could adopt the optimum settings as the new process settings and proceed to implement these settings.

TABLE 4.10 PREDICTION USING THE ADDITIVE MODEL

Factor	Starting Condition				Optimum Condition			
	Setting	Contribution† (dB)			Setting	Contribution† (dB)		
		Surface Defects	Thickness	Deposition Rate		Surface Defects	Thickness	Deposition Rate
A*	A_2	−4.74	3.39	0.01	A_1	21.13	3.60	−5.36
B	B_2	−2.08	0.00	0.66	B_2	−2.08	0.00	0.66
C	C_1	6.33	2.87	−1.31	C_1	6.33	2.87	−1.31
D	D_3	−4.68	−3.35	1.49	D_3	−4.68	−3.35	1.49
E*	E_1	−6.16	0.00	0.00	E_2	4.82	0.00	0.00
F*	F_1	0.00	−4.48	0.00	F_2	0.00	2.15	0.00
Overall Mean		−45.36	31.52	34.12		−45.36	31.52	34.12
Total		−56.69	29.95	34.97		−19.84	36.79	29.60

* Indicates the factors whose levels are changed from the starting to the optimum conditions.
† By *contribution* we mean the deviation from the overall mean caused by the particular factor level.

TABLE 4.11 RESULTS OF VERIFICATION EXPERIMENT

		Starting Condition	Optimum Condition	Improvement
Surface Defects	rms	600/cm^2	7/cm^2	
	η	−55.6 dB	−16.9 dB	38.7 dB
Thickness	std. dev.*	0.028	0.013	
	η'	31.1 dB	37.7 dB	6.6 dB
Deposition Rate	rate	60 Å/min	35 Å/min	
	η''	35.6 dBam	30.9 dBam	−4.7 dBam

* Standard deviation of thickness is expressed as a fraction of the mean thickness.

Follow-up Experiments

Optimization of a process or a product need not be completed in a single matrix experiment. Several matrix experiments may have to be conducted in sequence before completing a product or process design. The information learned in one matrix experiment is used to plan the subsequent matrix experiments for achieving even more improvement in the process or the product. The factors studied in such subsequent experiments, or the levels of the factors, are typically different from those studied in the earlier experiments.

From the case-study data on the polysilicon deposition process, temperature stood out as the most important factor—both for quality and productivity. The experimental data showed that high temperature leads to excessive formation of surface defects and nonuniform thickness. This led to identifying the type of temperature controller as a potentially important control factor. The controller used first was an underdamped controller, and, consequently, during the initial period of deposition, the reactor temperature rose significantly above the steady-state set-point temperature. It was then decided to try a critically damped controller. Thus, an auxiliary experiment was conducted with two control factors: (1) the type of controller, and (2) the temperature setting. This experiment identified the critically damped controller as being significantly better than the underdamped one.

The new controller allowed the temperature setting to be increased to $T_0 - 10$ °C while keeping the surface defect count below 1 defect/unit area. The higher temperature also led to a deposition rate of 55Å/min rather than the 35Å/min that was observed in the initial verification experiment. Simultaneously, a standard deviation of thickness equal to 0.007 times the mean thickness was achieved.

Range of Applicability

In any development activity, it is highly desirable that the conclusions continue to be valid when we advance to a new generation of technology. In the case study of the polysilicon deposition process, this means that having developed the process with 4-inch wafers, we would want it to be valid when we advance to 5-inch wafers. The process developed for one application should be valid for other applications. Processes and products developed by the Robust Design method generally possess this characteristic of design transferability. In the case study, going from 4-inch wafers to 5-inch wafers was achieved by making minor changes dictated by the thermal capacity calculations. Thus, a significant amount of development effort was saved in transferring the process to the reactor that handled 5-inch wafers.

4.9 SUMMARY

Optimizing the product or process design means determining the best architecture, levels of control factors, and tolerances. Robust Design is a methodology for finding the

optimum settings of control factors to make the product or process insensitive to noise factors. It involves eight major steps which can be grouped as planning a matrix experiment to determine the effects of the control factors (Step 1 through 5), conducting the matrix experiment (Step 6), and analyzing and verifying the results (Steps 7 and 8).

- **Step 1.** Identify the main function, side effects and failure modes. This step requires engineering knowledge of the product or process and the customer's environment.

- **Step 2.** Identify noise factors and testing conditions for evaluating the quality loss. The testing conditions are selected to capture the effect of the more important noise factors. It is important that the testing conditions permit a consistent estimation of the sensitivity to noise factors for any combination of control factor levels. In the polysilicon deposition case study, the effect of noise factors was captured by measuring the quality characteristics at three specific locations on each of three wafers, appropriately placed along the length of the tube. Noise orthogonal array and compound noise factor are two common techniques for constructing testing conditions. These techniques are discussed in Chapter 8.

- **Step 3.** Identify the quality characteristic to be observed and the objective function to be optimized. Guidelines for selecting the quality characteristic and the objective function, which is generically called S/N ratio, are given in Chapters 5 and 6. The common temptation of using the percentage of products that meet the specification as the objective function to be optimized should be avoided. It leads to orders of magnitude reduction in efficiency of experimentation. While optimizing manufacturing processes, an appropriate throughput characteristic should also be studied along with the quality characteristics because the economics of the process is determined by both of them.

- **Step 4.** Identify the control factors and their alternate levels. The more complex a product or a process, the more control factors it has and vice versa. Typically, six to eight control factors are chosen at a time for optimization. For each control factor two or three levels are selected, out of which one level is usually the starting level. The levels should be chosen sufficiently far apart to cover a wide experimental region because sensitivity to noise factors does not usually change with small changes in control factor settings. Also, by choosing a wide experimental region, we can identify good regions, as well as bad regions, for control factors. Chapter 6 gives additional guidelines for choosing control factors and their levels. In the polysilicon deposition case study, we investigated three levels each of six control factors. One of these factors (cleaning method) had discrete levels. For four of the factors the ratio of the largest to the smallest levels was between three and five.

- **Step 5.** Design the matrix experiment and define the data analysis procedure. Using orthogonal arrays is an efficient way to study the effect of several control factors simultaneously. The factor effects thus obtained are valid over the

experimental region and it provides a way to test for the additivity of the factor effects. The experimental effort needed is much smaller when compared to other methods of experimentation, such as guess and test (trial and error), one factor at a time, and full factorial experiments. Also, the data analysis is easy when orthogonal arrays are used. The choice of an orthogonal array for a particular project depends on the number of factors and their levels, the convenience of changing the levels of a particular factor, and other practical considerations. Methods for constructing a suitable orthogonal array are given in Chapter 7. The orthogonal array L_{18}, consisting of 18 experiments, was used for the polysilicon deposition study. The array L_{18} happens to be the most commonly used array because it can be used to study up to seven 3-level and one 2-level factors.

- **Step 6**. Conduct the matrix experiment. Levels of several control factors must be changed when going from one experiment to the next in a matrix experiment. Meticulousness in correctly setting the levels of the various control factors is essential—that is, when a particular factor has to be at level 1, say, it should not be set at level 2 or 3. However, one should not worry about small perturbations that are inherent in the experimental equipment. Any erroneous experiments or missing experiments must be repeated to complete the matrix. Errors can be avoided by preparing the experimenter's log and data sheets prior to conducting the experiments. This also speeds up the conduct of the experiments significantly. The 18 experiments for the polysilicon deposition case study were completed in 9 days.

- **Step 7**. Analyze the data, determine optimum levels for the control factors, and predict performance under these levels. The various steps involved in analyzing the data resulting from matrix experiments are described in Chapter 3. S/N ratios and other summary statistics are first computed for each experiment. (In Robust Design, the primary focus is on maximizing the S/N ratio.) Then, the factor effects are computed and ANOVA performed. The factor effects, along with their confidence intervals, are plotted to assist in the selection of their optimum levels. When a product or a process has multiple quality characteristics, it may become necessary to make some trade-offs while choosing the optimum factor levels. The observed factor effects together with the quality loss function can be used to make rational trade-offs. In the polysilicon case study, the data analysis indicated that levels of three factors—deposition temperature (A), settling time (E), and cleaning method (F)—be changed, while the levels of the other five factors be kept at their starting levels.

- **Step 8**. Conduct the verification (confirmation) experiment and plan future actions. The purpose of this final and crucial step is to verify that the optimum conditions suggested by the matrix experiments do indeed give the projected improvement. If the observed and the projected improvements match, we adopt the suggested optimum conditions. If not, then we conclude that the additive model underlying the matrix experiment has failed, and we find ways to correct that problem. The corrective actions include finding better quality characteristics, or signal-to-noise ratios, or different control factors and levels, or studying a few

specific interactions among the control factors. Evaluating the improvement in quality loss, defining a plan for implementing the results, and deciding whether another cycle of experiments is needed are also a part of this final step of Robust Design. It is quite common for a product or process design to require more than one cycle of Steps 1 through 8 for achieving needed quality and cost improvement. In the polysilicon deposition case study, the verification experiment confirmed the optimum conditions suggested by the data analysis. In a follow up Robust Design cycle, two control factors were studied—deposition temperature and type of temperature controller. The final optimum process gave nearly two orders of magnitude reduction in surface defects and a 4-fold reduction in the standard deviation of the thickness of the polysilicon layer.