ROBUST DESIGN: A COST-EFFECTIVE METHOD FOR IMPROVING MANUFACTURING PROCESSES

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Robust design is a method for making a manufacturing process less sensitive to manufacturing variations. Because it reduces variation by reducing the influence of sources of variation, not by controlling them, robust design is a cost-effective technique for improving process quality. The method uses small, statistically planned experiments to vary the settings of key process control parameters. For each combination of control parameter settings in the experiment, process performance characteristics are measured to reflect the effects of manufacturing variation. Then, simple plots or tables are used to predict the control parameter settings that minimize these effects. A small follow-up experiment confirms the prediction. This paper describes how to apply the basic robust design method to improve process quality.

The Central Idea

A main cause of poor yield in manufacturing processes is manufacturing variation. These manufacturing variations include variation in temperature or concentration within a production batch, variation in raw materials, and drift of process parameters. The more sensitive a process is to these variations, the more expensive it is to control.

The method described in this paper, robust design, is a cost-effective approach to improve yield. It uses statistically planned experiments to identify process control parameter settings that reduce the process's sensitivity to manufacturing variation. This method is based on the technique of robust design developed by Professor Genichi Taguchi, a Japanese expert on quality.

What is the central idea of robust design? The easiest way to explain it is to look at how robust design is improving the process for making optical filters. These filters, which are used in wavelength-division multiplexers, consist of a quartz substrate coated with thin layers of titanium dioxide and silicon dioxide.

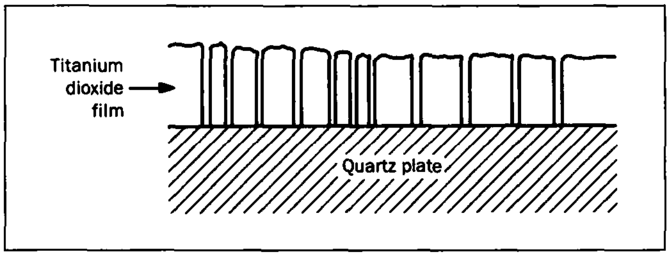


Figure 1. Cross section of a simple filter with only one film layer on a quartz substrate.

Variability of the filter's index of refraction in manufacture and in the field is a major problem, and one cause is the change in relative humidity in the factory and under field-use conditions. Figure 1 shows a simplified filter cross section with only one layer of titanium dioxide. Water molecules from the environment condense into pores in the film and change the filter's overall index of refraction.

To solve this problem, we could keep the relative humidity constant by building an hermetic seal around the filter. But this is a difficult and expensive solution. Instead, we are taking another approach: Design the filter-making process so that the film is dense with few crevices to trap water molecules. Thus, the filter's index of refraction will be less sensitive to humidity changes.

This idea—make a product or process insensitive to variation—is the essence of robust design. However, this paper concentrates on manufacturing process design. Although most ideas presented here also apply to product design, other optimization methods may be more appropriate.

In this paper, we formulate the robust-design problem and give four operational steps for applying the method. Then, we show how we used the method to improve an integrated-circuit (IC) fabrication process. Finally, we discuss the relationship between robust design and traditional uses of statistical design of experiments.

Formulating the Robust Design Problem

To define the objective of robust design more precisely, we need three concepts: functional characteristics, control parameters, and sources of noise.

Functional characteristics are basic, measurable quantities that determine how well the final product functions. For the optical-filter example, the film's index of refraction and absorption are two of the characteristics that determine how well the completed filter separates light of certain wavelengths.

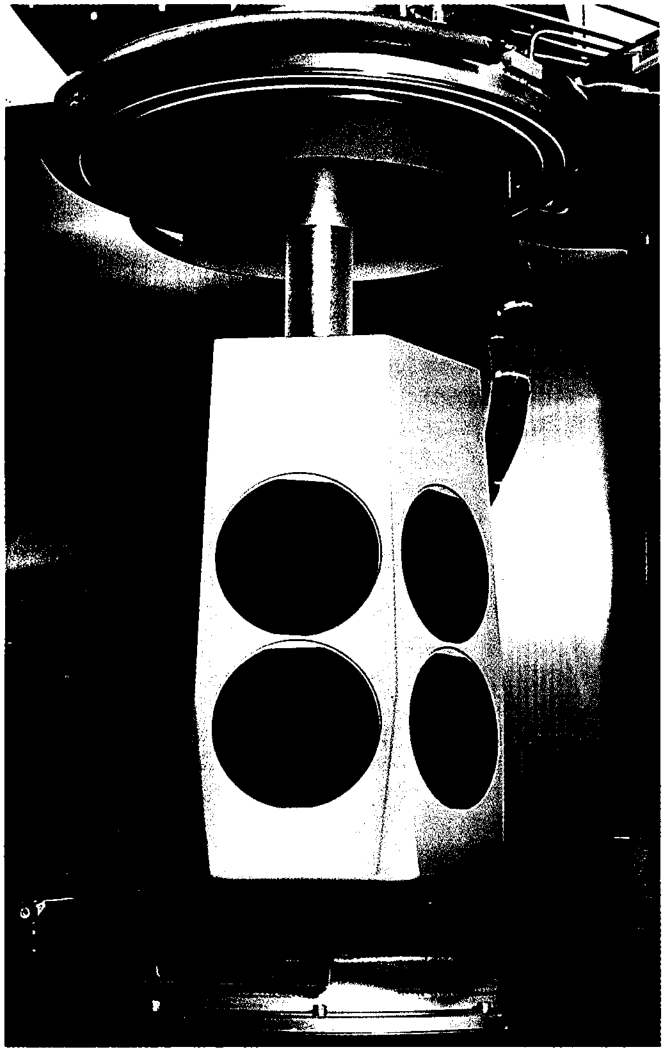
When we study a specific step of a manufacturing process, the functional characteristics are usually measurements that can be made on the incomplete product soon after that step.

The essence of robust design is to reduce variation of a product's or process's functional characteristics. (The average value of a functional characteristic is usually of secondary concern, because we can adjust it to the target after we minimize variability. In a later section, we will see how this was possible in the manufacture of IC wafers.) Two types of variables affect functional characteristics: control parameters and sources of noise.

Control parameters are the controllable process variables; their operating standards can be specified by the process engineers. In the optical-filter example, the control parameters include the temperature of the substrates and the method of cleaning the substrates.

In contrast, *sources of noise* are the variables that are impossible or expensive to control. Examples include temperature and humidity variations in the factory, drift in process control parameters, and variation in raw materials. They, in turn, cause variations in the product's functional characteristics.

The objective in robust design is to find those control parameter settings where noise has a minimal effect on the functional characteristics. As in the optical-filter example, the key idea is to reduce functional characteristic



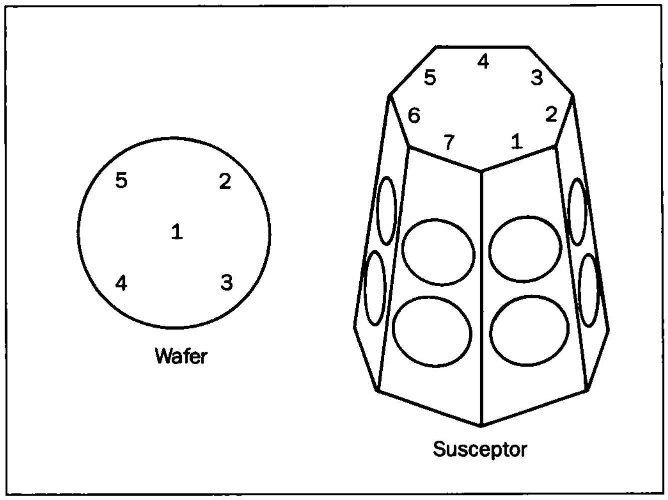


Figure 2. Plan for studying the effect of noise on the epitaxial process. Five measurements of epitaxial thickness are made on each of 14 wafers. The photograph shows the wafers mounted on the susceptor.

sensitivity by making the process insensitive to noise rather than by controlling the sources of noise.

To attain this objective, we systematically vary the control parameters in an experiment and measure the effect of noise for each experimental run. Then we use the results to predict which control parameter settings will make the process insensitive to noise.

Operational Steps for Robust Design

The robust design method can be applied by following four operational steps:

1. List the functional characteristics, control parameters, and sources of noise.
2. Plan the experiment:
   a. How will control parameter settings be varied?
   b. How will the effect of noise be measured?
3. Run the experiment and use the results to predict improved control parameter settings.
4. Run a confirmation experiment to check the prediction.

The next section describes each step and how it was applied to improve the process of growing an epitaxial layer on silicon wafers used in IC fabrication.

Epitaxial-Process Example

A first step in processing silicon wafers for IC devices is to grow an epitaxial layer on polished silicon wafers. As Figure 2 shows, a batch of 14 wafers is processed together. Two wafers are mounted on each side, or facet, of a seven-sided cylindrical structure, called a susceptor.

The susceptor is positioned inside a metal bell jar. As the susceptor rotates, chemical vapors are introduced through nozzles near the top of the jar. The susceptor and wafers are heated to an elevated temperature, which is maintained until the epitaxial layer is thick enough.

Table I. Initial and Test Settings of Each Control Parameter

Control Parameter	Initial Setting	Test Setting 0	Test Setting 1
A. Susceptor-rotation method	Oscillating	Continuous	Oscillating
B. Code of wafers	—	668G4	678D4
C. Deposition temperature	1215°C	1210°C	1220°C
D. Deposition time	Low	High	Low
E. Arsenic flow rate	57%	55%	59%
F. Hydrochloric acid etch temperature	1200°C	1180°C	1215°C
G. Hydrochloric acid flow rate	12%	10%	14%
H. Nozzle position	4	2	6

The process specifications called for a layer between 14 and 15 micrometers thick, but the actual variation from the ideal 14.5 micrometers was greater than this. Therefore, we needed to minimize nonuniformity in the epitaxial layer, yet keep the average thickness as close to the ideal as possible.

While working with the engineers responsible for the process, we conducted a robust design experiment to reduce the variability, but still keep the average thickness near 14.5 micrometers. We identified eight key process-control parameters and, using 16 batches of wafers, evaluated the epitaxial layer's average thickness and nonuniformity for two test settings of each parameter.

The experiment's results showed that two control parameters, nozzle position and susceptor-rotation method, determined the epitaxial layer's uniformity. The results also showed that one parameter, deposition time, had a large effect on average thickness but no effect on uniformity. A follow-up experiment confirmed that the new settings for nozzle position and rotation method, determined in the first experiment, reduced nonuniformity about 60 percent. The change to new settings did not increase cost.

The next subsections describe how the four operational steps of robust design were followed to obtain these new parameter settings.

Step 1—List functional characteristics, control parameters, and sources of noise. Most processes have many functional characteristics. For example, the epitaxial process has two important functional characteristics: epitaxial thickness and epitaxial resistivity. Both were studied, but this paper will discuss only the results for epitaxial thickness.

Although every process has many control parameters, we usually cannot study them all simultaneously. Most robust design experiments study five to ten control parameters at a time.

In the epitaxial-process experiment, we studied eight parameters; A through H represent the code letters used in this paper for these parameters:

A. Susceptor-rotation method
B. Wafer code
C. Deposition temperature
D. Deposition time
E. Arsenic gas flow rate
F. Hydrochloric acid etch temperature
G. Hydrochloric acid flow rate
H. Nozzle position.

Parameter B, wafer code, is not a control parameter in the usual sense. Many different codes of wafers must pass through the epitaxial process. However, including the code as a control parameter allowed us to identify the settings of other control parameters that produced uniform epitaxial layers on a variety of wafer codes.

We tested each parameter at two settings. Table I shows the initial settings and the two test settings.

The principal sources of noise in the epitaxial process were uneven temperature, vapor-concentration, and vapor-composition profiles inside the bell jar. Because of these uneven profiles, the epitaxial-layer thickness was different on wafers at different locations on the susceptor. The difference was largest between wafers at the top and bottom positions on each facet.

Table II. Control Array for Epitaxial Process Experiment

Experimental Run	Control Parameter							
	A	B	C	D	E	F	G	H
1	Cont	668G4	1210	High	55	1180	10	2
2	Cont	668G4	1210	High	59	1215	14	6
3	Cont	668G4	1220	Low	55	1180	14	6
4	Cont	668G4	1220	Low	59	1215	10	2
5	Cont	678D4	1210	Low	55	1215	10	6
6	Cont	678D4	1210	Low	59	1180	14	2
7	Cont	678D4	1220	High	55	1215	14	2
8	Cont	678D4	1220	High	59	1180	10	6
9	Osclt	668G4	1210	Low	55	1215	14	2
10	Osclt	668G4	1210	Low	59	1180	10	6
11	Osclt	668G4	1220	High	55	1215	10	6
12	Osclt	668G4	1220	High	59	1180	14	2
13	Osclt	678D4	1210	High	55	1180	14	6
14	Osclt	678D4	1210	High	59	1215	10	2
15	Osclt	678D4	1220	Low	55	1180	10	2
16	Osclt	678D4	1220	Low	59	1215	14	6

NOTE: The control array specifies the experimental runs.

Step 2—Plan the experiment. In a robust design experiment, we vary the settings of the control parameters simultaneously in a few experimental runs. For each run, we make multiple measurements of the functional characteristic to evaluate the process's sensitivity to noise.

Therefore, planning the experiment is a two-part step that involves deciding how to vary the parameter settings and how to measure the effect of noise.

Step 2a—Plan how control parameter settings will be varied. In step 1, we identified eight control parameters as potentially important in the epitaxial process. Because we would test each parameter at two settings, we would need 2^8, or 256, experimental runs to evaluate every possible combination of settings. Clearly, this would be too expensive and time consuming. Fortunately, we could choose a small subset of these runs and still obtain the most important information about the control parameters.

In the epitaxial-process example, we conducted only 16 of the 256 possible runs. Table II, called the *control array* for the experiment, shows the control-parameter

Table III. A One-parameter-at-a-time Experiment

Experimental Run	Control Parameter							
	A	B	C	D	E	F	G	H
1	Cont	668G4	1210	High	55	1180	10	2
2	Osclt	668G4	1210	High	55	1180	10	2
3	Osclt	678D4	1210	High	55	1180	10	2
4	Osclt	678D4	1220	High	55	1180	10	2
5	Osclt	678D4	1220	Low	55	1180	10	2
6	Osclt	678D4	1220	Low	59	1180	10	2
7	Osclt	678D4	1220	Low	59	1215	10	2
8	Osclt	678D4	1220	Low	59	1215	14	2
9	Osclt	678D4	1220	Low	59	1215	14	6

NOTE: This is not a balanced experiment.

settings for the 16 runs.

This control array has an important property: it is *balanced.* That is, for every pair of parameters, each combination of test settings appears an equal number of times. For example, consider the parameters: deposition temperature (C) and deposition time (D). The combinations (C = 1210°C, D = High), (C = 1210°C, D = Low), (C = 1220°C, D = High), and (C = 1220°C, D = Low) each occur four times in columns 3 and 4.

Because of this balancing property, it is meaningful to compare the two deposition-temperature test settings over a range of test settings for deposition time and each of the other control parameters in the experiment. Therefore, we can draw separate conclusions about each control parameter from the results of the experiment.

By contrast, it can be difficult to draw conclusions from the results of an unbalanced experiment. For example, a "one-parameter-at-a-time" experiment, the type most commonly run, is unbalanced. In such experiments, one control parameter is varied at a time, while all others are held fixed. Table III shows this unbalanced experiment for the epitaxial-process example.

If we took this approach, we would compare deposition-temperature settings (C) using the results of runs 3 and 4. However, the comparison would be valid *only* when the other seven control parameters are fixed at their values in these two runs.

This example also illustrates a second advantage

Table IV. Orthogonal Array OA_{16} (2^{15})

Experimental	Column Assignment for Control Parameter (A-H)														
	A	B		C			D	E			F		G	H	
Run	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
3	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1
4	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0
5	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1
6	0	1	1	0	0	1	1	1	1	0	0	1	1	0	0
7	0	1	1	1	1	0	0	0	0	1	1	1	1	0	0
8	0	1	1	1	1	0	0	1	1	0	0	0	0	1	1
9	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
10	1	0	1	0	1	0	1	1	0	1	0	1	0	1	0
11	1	0	1	1	0	1	0	0	1	0	1	1	0	1	0
12	1	0	1	1	0	1	0	1	0	1	0	0	1	0	1
13	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0
14	1	1	0	0	1	1	0	1	0	0	1	1	0	0	1
15	1	1	0	1	0	0	1	0	1	1	0	1	0	0	1
16	1	1	0	1	0	0	1	1	0	0	1	0	1	1	0

NOTE: This assignment of control parameters A through H to the columns of OA_{16} provides a resolution-IV plan.

of balanced experiments. In the balanced epitaxial-layer experiment (Table II), we use the results of all 16 runs to compare deposition-temperature settings (C). This is more precise than the one-parameter-at-a-time comparison, which uses only two runs.

Control arrays that have the desirable balancing property can be constructed easily from special tables called orthogonal arrays (OAs). We constructed the control array for the epitaxial-process experiment from the orthogonal array, OA_{16} (Table IV).

To obtain the control array, we assigned the control parameters to columns 1, 2, 4, 7, 8, 11, 13, and 14 of OA_{16}, and replaced the symbols 0 and 1 with each parameter's test settings. This particular assignment of parameters to the columns of OA_{16} produces a *resolution-IV plan*; it ensures that the experiment will give good estimates of each control parameter's first-order (linear) effects. (For more on the resolution of experiment plans, see Chapter 12 of Box, Hunter, and Hunter.[1])

Although OA_{16} is one of the most frequently used orthogonal arrays, there are many other useful arrays. A particularly valuable one is OA_8, which permits studying up

Table V. Mean and Log of Variance of Epitaxial Thickness for Each Test Run

Experimental Run	Mean $\bar{y}$ (μm)	Log of Variance $\log s^2$
1	14.821	−0.4425
2	14.888	−1.1989
3	14.037	−1.4307
4	13.880	−0.6505
5	14.165	−1.4230
6	13.860	−0.4969
7	14.757	−0.3267
8	14.921	−0.6270
9	13.972	−0.3467
10	14.032	−0.8563
11	14.843	−0.4369
12	14.415	−0.3131
13	14.878	−0.6154
14	14.932	−0.2292
15	13.907	−0.1190
16	13.914	−0.8625

to four control parameters at two levels each in only eight experimental runs. Arrays such as OA_{18} and OA_{27} are useful when most control parameters have three test settings. Phadke, Kackar, and others[2] used OA_{18} to construct the control array for an experiment to improve a window-photolithography process.

Step 2b—Plan how the effect of noise will be measured. In the epitaxial-layer experiment, a major cause of variation in epitaxial thickness was uneven distribution of chemical vapors from the top to the bottom of the bell jar. To reflect this variation, we systematically measured the epitaxial thickness of wafers at top and bottom locations on each susceptor facet.

Our plan was to measure epitaxial thickness at five places (Figure 2) on each of the 14 wafers, a total of 70 measurements from one run. We did this for all 16 experimental runs in the control array.

This plan for measuring the effect of noise is typical of procedures followed in most robust-design experiments for process improvement. Usually, we measure the effect of noise by taking multiple measurements of the functional characteristic at different positions on a unit and on several units in the experimental run. It is important to plan these measurements to reflect the effect of noise and follow the same plan for each experimental run, so comparisons between the runs are fair.

Step 3—Run the experiment and use the results to predict improved control parameter settings. If the experiment is well-planned and run according to plan, the analysis needed to predict improved parameter settings is simple.

As described in step 2, we made 70 measurements of epitaxial thickness for each of the 16 test runs in Table II. For each run, we calculated the mean and variance of these measurements. If y_1 through y_{70} represent the 70 measurements for one test run, the mean is

$$\bar{y} = \frac{1}{70}\sum_{i=1}^{70} y_i,$$

and the variance is

$$s^2 = \frac{1}{69}\sum_{i=1}^{70} (y_i - \bar{y})^2.$$

Table V shows the values of $\bar{y}$ and $\log s^2$ for each test run. (The logarithm of s^2 is taken to improve statistical properties of the analysis.)

The experiment's objective was to make the epitaxial-thickness variance small and make the mean thickness close to 14.5 micrometers. We focused on reducing the variance of epitaxial thickness. After minimizing variance, we could adjust deposition time to get a 14.5-micrometer mean thickness.

To reduce the variance of epitaxial thickness, we identified the control parameters that have the largest effect on $\log s^2$ and set them at the settings that minimized $\log s^2$. Table VI and Figure 3 display the average values of $\log s^2$ for the test settings of all eight control parameters.

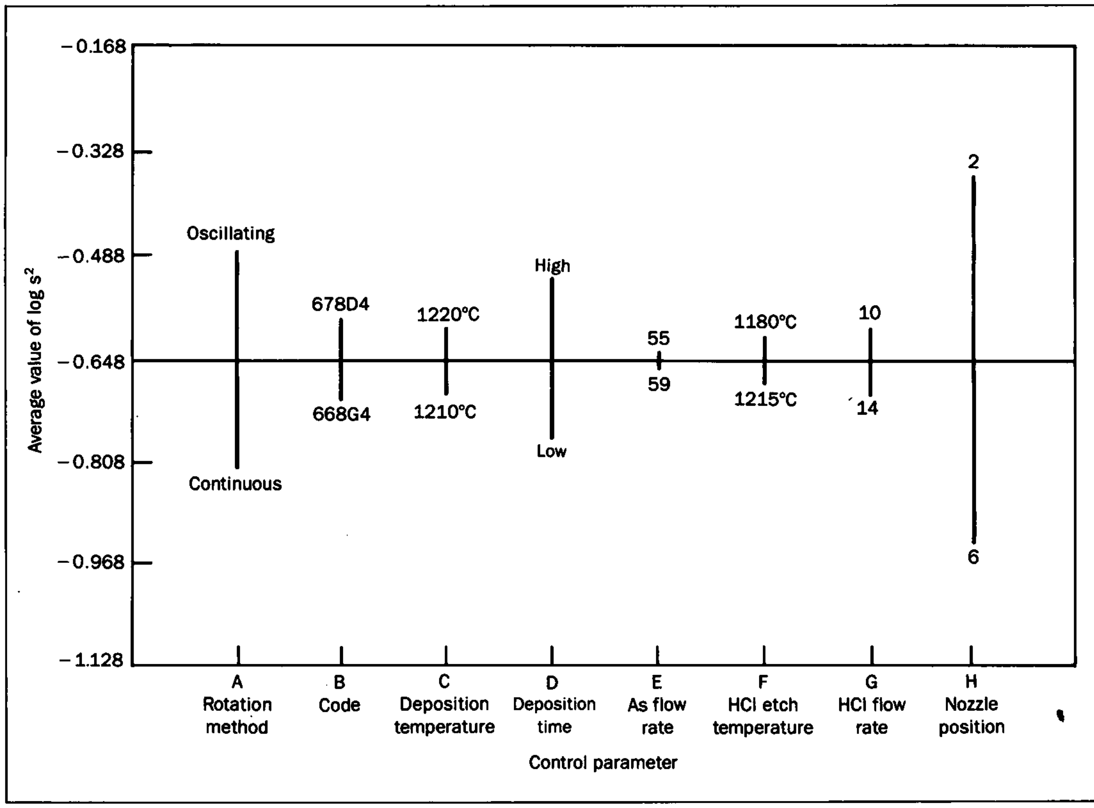


Figure 3. Average values of log s^2 at each setting of control parameters.

For example, consider design parameter A, susceptor-rotation method. Its setting is *continuous* in runs 1 through 8 and *oscillating* in runs 9 through 16.

From Table VI, the average of the values of log s^2 for runs 1 through 8 is

$$-0.8245 = \frac{-0.4425 + -1.1989 + \cdots + -0.6270}{8}.$$

Likewise, the average of the values of log s^2 for runs 9 through 16 is

$$-0.4724 = \frac{-0.3467 + -0.8563 + \cdots + -0.8625}{8}.$$

Because log s^2 measures the uniformity of epitaxial thickness, the better setting of each control parameter is the one that gives the smaller average value of log s^2. For example, continuous rotation (setting 0) of the susceptor is better than oscillation (setting 1) because, on the average, it gives more uniform epitaxial layers.

We compared the test settings of the other control parameters in the same way. However, we changed each parameter's setting only if this change had a large effect on the variability of epitaxial thickness. When a control parameter is tested at two settings, the magnitude of its effect on variability is measured by the difference between the average values of log s^2 at those settings.

The lengths of the bars in Figure 3 provide a visual summary of the magnitude of each control parameter's effect. (The horizontal line at -0.648 is the average value of log s^2 over all 16 runs.) Because nozzle position and rotation method had greater effect than the other six control parameters, we changed the settings of only these two parameters. All others were left at their initial settings.

Step 4—Run a confirmation experiment to check the prediction. When we used OA_{16} to construct the control array for the epitaxial-process experiment, we assumed that the

Table VI. Average Value of log s^2 at Different Test Settings

Control Parameter	Average log s^2 Test Setting 0	Test Setting 1	Difference
A. Susceptor-rotation method	−0.8245	−0.4724	0.3521
B. Code of wafers	−0.7095	−0.5875	0.1220
C. Deposition temperature	−0.7011	−0.5958	0.1053
D. Deposition time	−0.5237	−0.7732	−0.2495
E. Arsenic gas flow rate	−0.6426	−0.6543	−0.0117
F. Hydrochloric acid etch temperature	−0.6126	−0.6843	−0.0717
G. Hydrochloric acid flow rate	−0.5980	−0.6989	−0.1008
H. Nozzle position	−0.3656	−0.9313	−0.5658

relationship between log s^2 and the control parameters was predominantly linear. This array does allow for some nonlinearity, of a type called interaction between pairs of control parameters. However, if the relationship is highly nonlinear, the new settings found in step 3 might not be an improvement over the initial settings.

To guard against this possibility, a small follow-up experiment was conducted that included the new control parameter settings and, as a benchmark, the initial settings to confirm the prediction. The only differences in new and initial settings were those for nozzle position and rotation method. We conducted three independent test runs at each setting and calculated the mean and the log of the variance of epitaxial thickness from the results. Table VII shows the average values of the mean, $\bar{y}$, and the log variance, log s^2, at the new and the initial control parameter settings.

The confirmation experiment's results show that the new settings reduced the variance of epitaxial thickness about 60 percent. There was almost no difference in the mean thickness at the two settings, because deposition time was not changed in the experiment.

In general, a confirmation experiment is essential before making a change to the manufacturing process, based on the results of a robust design experiment. Experiments that study many control parameters in a few runs are powerful tools for making improvements. However, many assumptions are made in planning these small experiments, and the confirmation experiment is insurance against incorrect assumptions.

Finding Mean-Adjustment Parameters

In many manufacturing processes, one or more control parameters can be used to change a functional characteristic's mean, or average value, without affecting the process's variability. When these mean-adjustment control parameters[3] exist, we can choose settings of the other control parameters to minimize variability, while ignoring the mean. Then, we use the adjustment parameter to move the mean to target.

So, the key characteristics of a mean-adjustment parameter are a small effect on variability and a large effect on the mean.

In the epitaxial process, engineers use deposition time to control the mean epitaxial thickness. One goal of our robust design experiment was to reduce the process variability, but another was to verify that deposition time could indeed be used to adjust the mean epitaxial thickness without affecting its variability.

From Figure 3, we can see that deposition time has a smaller effect on the variance of epitaxial thickness than nozzle position and rotation method. To check that deposition time has a strong effect on the mean epitaxial thickness, we analyze $\bar{y}$ in the same way that log s^2 was analyzed in step 3.

Table VIII and Figure 4 show the average values of $\bar{y}$ at each control parameter setting. In Figure 4, notice that deposition time has the largest effect on the mean epitaxial thickness, $\bar{y}$.

After this analysis, we adopted the new control parameter settings for the epitaxial process and adjusted deposition time to make the mean epitaxial thickness equal 14.5 micrometers. Notice that, if we changed the target

Table VII. Confirmation Experiment

Experimental Run	Control Parameter								Average Value		
	A	B	C	D	E	F	G	H	$\bar{y}$	$\log s^2$	s^2
Initial settings	Osclt	678D4	1215	Low	57	1200	12	4	14.10	−0.845	0.143
New settings	Cont	678D4	1215	Low	57	1200	12	6	14.17	−1.244	0.057

thickness, we could adjust deposition time accordingly, and the settings of the other control parameters would still give a small variance about this new target.

Summary and Discussion

In this paper, we outlined the basic steps of the robust design method. Box, Hunter, and Hunter[1] provide more details on how to plan experiments, and Kackar[4] gives a thorough discussion of robust design. Also, the book by Taguchi and Wu[5] includes some examples of Japanese applications of this method.

Besides the examples described here (and by Phadke[6] in this issue), the robust design method has been used to improve many other processes in AT&T. Examples include a window-photolithography process,[2] the application of photoresist in hybrid IC manufacture, and reactive-ion etching and aluminum etching processes for 256K RAM manufacture.

Most AT&T applications of robust design have been to improve process designs rather than product designs. Although some details may be different, the general ideas apply to product design as well. For example, the Japanese used this method to improve the design of a truck steering mechanism.[5]

However, for some products—such as electrical circuits—we know what function relates the product's functional characteristic to its control parameters and major sources of noise. For such products, other optimization methods that take advantage of the knowledge of this function and its derivatives may often be more efficient.

The robust design method uses an established statistical tool—the design of experiments—to help solve an important engineering problem: reducing variability caused by manufacturing variation. This use of designed experiments is Professor Genichi Taguchi's major contribution.

Statistically designed experiments have been used to improve industrial processes for more than 50 years,[1,7,8] but most applications have focused on the mean values of the process's functional characteristics. In many process improvement applications, we can easily change the mean value using a mean-adjustment parameter. The yield of a manufacturing process is more closely linked to the process's variability, and robust design is a method for reducing that variability without increasing process cost.

Acknowledgment

In this paper, we used two experiments conducted by AT&T's Technology Systems Group to illustrate the key ideas of robust design. We want to thank the following engineers, who were responsible for the experiments: D. G. Coult, S. M. Fisher, J. R. Mathews, D. H. Myers, and J. L. Pascuzzi.

Table VIII. Average Value of $\bar{y}$ at Different Test Settings

Control Parameter	Average $\bar{y}$ Test Setting 0	Test Setting 1	Difference
A. Susceptor-rotation method	14.4161	14.3616	–0.0545
B. Code of wafers	14.3610	14.4167	0.0556
C. Deposition temperature	14.4435	14.3342	–0.1094
D. Deposition time	14.8069	13.9709	–0.8359
E. Arsenic gas flow rate	14.4225	14.3552	–0.0674
F. Hydrochloric acid etch temperature	14.3589	14.4189	0.0600
G. Hydrochloric acid flow rate	14.4376	14.3401	–0.0975
H. Nozzle position	14.3180	14.4597	0.1417

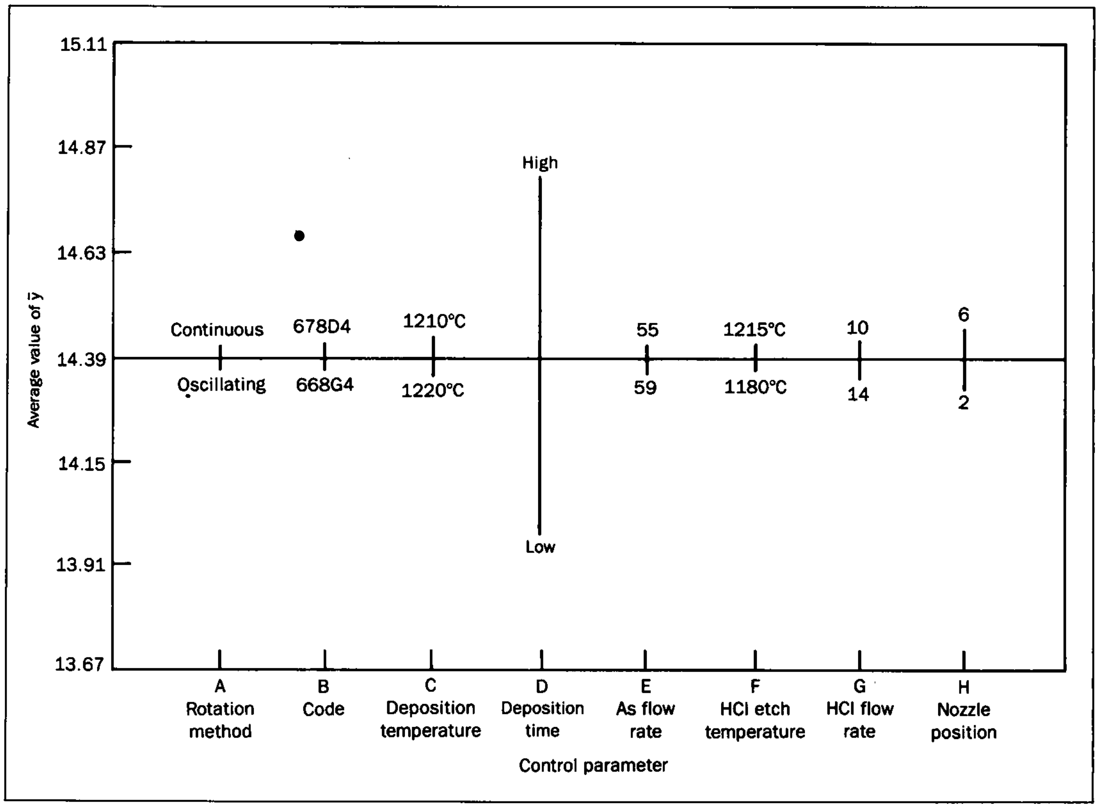


Figure 4. Average values of $\bar{y}$ at each setting of control parameters.

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