How to Optimize and Control the Wire Bonding Process: Part I

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ABSTRACT

To help process engineers improve, optimize, and control the wire bonding process, proven statistical analysis tools/techniques are provided to deal with four stages of a process. Part I covers developing a new process. Part II will discuss a process running at low yield, improving a marginally acceptable process, and maintaining process quality.

Wire bonding is an extremely high yield, high speed, automated manufacturing process. Modern wire bonders are capable of bonding 8 to 10 wires/sec and typical monthly throughput can exceed 500,000 devices. It's not unusual to see device yields approaching 99.99 percent with wire yields exceeding 99.999 percent. Total bonding defects are less than 100 parts per million (ppm), but real process optimization is required to achieve and maintain these yields. This article will discuss methods used to improve, optimize, and control the wire bonding process. These include design of experiments, response surface techniques, process capability studies, and control charts for high yield processes.

The use of designed experiments for screening wire bonding process variables and for optimizing the process will be described. They have been used extensively at K&S to establish new wire bonding processes and to design new, high reliability wire bonders such as the Model 1484XQ. They are easy to use and their data are easily analyzed. Process capability (and its relationship to design specifications) is also defined and discussed.

Many engineers have discovered the shortcomings of visual wire bond inspection. A logical alternative has been the use of statistical process control (SPC) control charts, but, unfortunately, conventional charts do not work well for very high yield processes. At defect levels below 1 percent, each defect generated results in an out-of-control signal. A new type of control chart has been proposed by T.N. Goh [1]. It is based on cumulative defects and it sets more appropriate levels for upper and lower control limits.

The combination of optimization methods mentioned above gives a reasonable, structured approach to controlling the wire bonding manufacturing process. With careful analysis of the observed defects and diligent attention to the largest defect generators, these methods will enable defects to be controlled and the process to be stabilized.

To help the reader follow the use of these tools/methods, step by step, we describe four possible situations in which a process needs to be developed, improved, or maintained. They are:

- New process development.
- Improvement of a process running at low yield.
- Improvement and stabilization of a marginally acceptable process.
- Maintaining a process at an acceptable quality level.

As each situation is covered, we will discuss in detail the tools required, provide a brief statistical explanation, suggest further reading, and offer examples.

Developing a New Process

In this section we will describe the development of a new process. This method can be used for a new package type, new die, new wire bonder, etc.

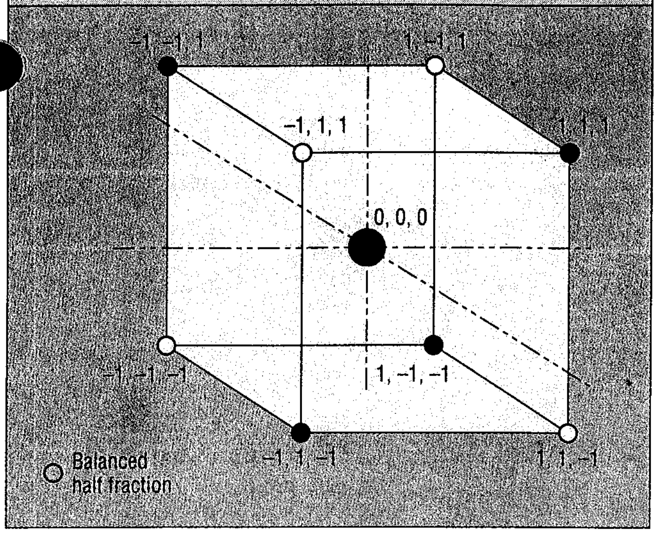
Design of Experiments

Design of experiments (DOX) is a topic within the field of statistics [2]. It provides an efficient, structured approach to the problem of controlling a process with a large number of variables like wire bonding. By enabling one to efficiently explore the bonding process using many variables, designed experiments allow the engineer to determine which of the variables have significant effects on the process. Once they are identified through screening experiments, additional experiments provide mapping of the response surface and lead to efficient process optimization.

In contrast, a traditional method for conducting scientific experiments has been to hold everything constant while changing only one variable at a time. Data variation could then be attributed to the shift in that variable. This method poses two problems: it is very time consuming, and it does not measure the interaction between two variables since they must be varied simultaneously to see the effect. Often these interaction effects are the strongest and most important factors in controlling a process.

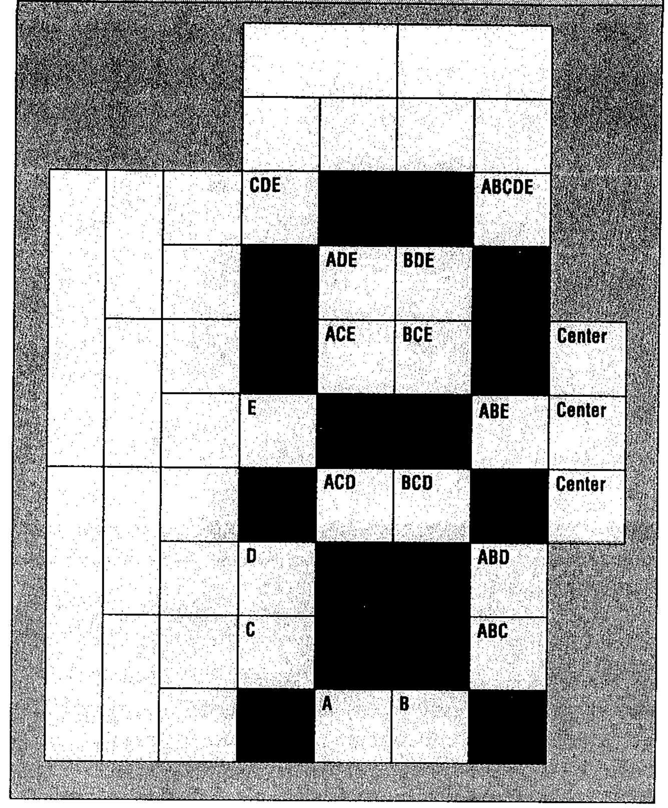
The designed experiment described here for creating a new process includes five variables. It allows screening of all five variables with only 19 samples. Using the traditional one variable at a time approach would require over 80 samples! In addition, with DOX it is now possible to measure interaction effects which may prove to be very important.

FIGURE 1



A three variable, two level factorial design. Variable levels are represented by numerals: -1 (low), 0 (center), and 1 (high).

FIGURE 2



Data sheet format for a half-factorial five variable DOX experiment.

Selection of Variables

Several classes of variables can be used in DOX. Some, such as programmable bonding parameters, can be changed easily over a numerical range. Not so with others like types of capillaries (basic designs) and materials (alloys). Programmable variables are selected for initial screening experiments; nonprogrammable, treatment variables are tested using multiple runs of the screening experiment.

To select variables for an initial wire bonding DOX, run the screening experiment using the principal wire bonding variables: ultrasonic power, bond force, temperature, bond time, and velocity. The results (responses) of the initial experiment will identify the major problems or defects. In subsequent experiments variables are chosen to address these problems. For example, if weak crescent bonds are detected, an experiment using crescent bond power, force, and time would be appropriate. Discovery of cratering would result in a choice of first bond variables. Variables with insignificant effects are also useful and eliminating them allows the effort to become more focused.

The level (setting) of each variable in an experiment can cover a large range. However, the intention is not to test the extremes of the process, but to sample a reasonable range of the values of interest. If a variable is significant and the results show that extreme values are desirable, subsequent experiments can explore this new range.

Running the Fractional Factorial DOX

One textbook experimental design that fits the wire bonding process very well is the fractional factorial [3]. It is easy to run and can normally be set up, run, tested, and analyzed in a day.

To illustrate factorial designs let us represent a simple version by the corners of a cube (Fig. 1). The corner points (cells) include all of the possible factorial combinations of three variables at two levels each. The four corners shown as solid balls are the ones that would be required for a half-fraction experiment. The fractional designs select a subset of cells that optimize the validity of the most important statistics (mean, main effects, and two level interactions) while sacrificing the validity of higher level interactions (three level and above). For most engineering work this represents a reasonable compromise.

The screening experiment is actually one-half a full factorial, five variable experiment (2^{5-1}). It requires 16 samples per experiment plus three additional center points. Each center point is the average value for each of the five variables in the experiment. Multiple center points are required in order to estimate process repeatability. Center points also estimate the curvature of the response surface. The difference between the mean of the three samples bonded at the center points and the mean of the 16 factorial points provides an estimate of the response surface curvature.

To begin the experiment, one determines what response measurements are most important to the new process. The responses should not be attribute (good/bad) data, they must be numeric variable measurements. Several different responses may be analyzed at the same time with this method. For example, pull strength data, loop heights, shear test values, and bond placement could all be studied on the same devices. At the end of the experiment, a separate graph/analysis will be produced for each response.

Figure 2 shows the format of the data sheet used for this experiment. Note that one-half of the response cells are not used (blackened). Nevertheless, with the half-fractional design, very little engineering information is lost.

Let us select five variables that are believed to be most important; choose a high, low, and center level for each variable, and write the variable names and levels on the DOX form as shown in Fig. 3. Additional variables can be studied in subsequent runs as insignificant variables are removed.

The letters in each cell only list the variables that are at

FIGURE 3

Bond time	Power	Bond Force	Temp = 150° C, Constant Vel. = 0.6 in./s	Temp = 150° C, Constant Vel. = 1.2 in./s	Temp = 200° C, Constant Vel. = 0.6 in./s	Temp = 200° C, Constant Vel. = 1.2 in./s	Center Pts.
Bond time = 20 ms	Power = 200 mW	Bond Force = 120 g	CDE $\bar{X}$ = 6.9 S.D. = 3.0			ABCDE $\bar{X}$ = 8.3 S.D. = 1.8	Temp = 175° C, Constant Vel. = 0.9 in./s, Time = 15 ms, Power = 160 mW, Force = 100 g
Bond time = 20 ms	Power = 200 mW	Bond Force = 80 g		ADE $\bar{X}$ = 8.0 S.D. = 2.3	BDE $\bar{X}$ = 7.8 S.D. = 3.0		
Bond time = 20 ms	Power = 120 mW	Bond Force = 120 g		ACE $\bar{X}$ = 9.2 S.D. = 1.3	BCE $\bar{X}$ = 8.6 S.D. = 1.4		Center 1 $\bar{X}$ = 8.1 S.D. = 1.4
Bond time = 20 ms	Power = 120 mW	Bond Force = 80 g	E $\bar{X}$ = 8.5 S.D. = 1.5			ABE $\bar{X}$ = 8.7 S.D. = 1.6	Center 2 $\bar{X}$ = 8.6 S.D. = 1.0
Bond time = 10 ms	Power = 200 mW	Bond Force = 120 g		ACD $\bar{X}$ = 8.5 S.D. = 1.8	BCD $\bar{X}$ = 8.6 S.D. = 1.4		Center 3 $\bar{X}$ = 8.6 S.D. = 1.5
Bond time = 10 ms	Power = 200 mW	Bond Force = 80 g	D $\bar{X}$ = 5.8 S.D. = 3.1			ABD $\bar{X}$ = 8.7 S.D. = 1.8	
Bond time = 10 ms	Power = 120 mW	Bond Force = 120 g	C $\bar{X}$ = 9.0 S.D. = 1.1			ABC $\bar{X}$ = 9.5 S.D. = 1.2	
Bond time = 10 ms	Power = 120 mW	Bond Force = 80 g		A $\bar{X}$ = 7.9 S.D. = 3.0	B $\bar{X}$ = 7.7 S.D. = 2.6		

Data sheet of Fig. 2 containing data gathered during development of the K & S Model 1484XQ Wire Bonder.

their high levels. In the cell named ABCDE all five of the variables are at their high level, in cell A only variable A is high and variables BCDE are at their low levels.

It is very important to randomize the running order of the 19 combinations (cells). The three center point cells must be spread throughout the run. Failure to randomize the run order leads to the possibility of false conclusions. The run order should be filled in on the cells of the DOX sheet.

Now the experiment should be run as planned, making any observations/notes on the DOX sheet during the run. When finished, the devices should be tested in the same order as the run sequence. It is acceptable to add responses after the run has been completed (i.e., additional visual measurements, chemical etching, etc.).

Typical pull test samples should include all wires on a low lead count package or at least 16 wires on a high lead count device. For shear testing, 10 bonds are usually tested. These test quantities are only guidelines to show the approximate number needed for different responses. The mean ($\bar{X}$) and standard deviation (S.D.) should now be calculated and entered for each cell on the DOX sheet and spread sheet template [4]. Any statistical software capable of analyzing a fractional factorial DOX may be used.

Figure 3 is an actual data sheet from an experiment conducted during the development of the K&S Model 1484XQ wire bonder. It shows the crescent bond variables studied, the level of each variable, the cell name, mean pull strength, and the pull strength S.D. Each mean and S.D. is based on a 30 lead test sample.

Table I is the analysis sheet from the same experiment. The top half of the sheet contains the data from the run sheet (Fig. 3). The data entered includes:

TABLE I

2^{5-1} Experiment Data Sheet

Cell*	Pull Strength Response Mean (g)	S.D. (g)
E	8.50	1.50
A	7.90	3.00
B	7.70	2.60
ABE	8.70	1.60
C	9.00	1.10
ACE	9.20	1.30
BCE	8.60	1.40
ABC	9.50	1.20
D	5.80	3.00
ADE	8.00	2.30
BDE	7.80	3.00
ABD	8.70	1.80
CDE	6.90	3.00
ACD	8.50	1.80
BCD	8.60	1.40
ABCDE	8.30	1.80
CENTER1	8.60	1.00
CENTER2	8.10	1.40
CENTER3	8.60	1.50

* Samples per cell = 30

Main Effects and Interactions (g)

	(g)	
Mean	8.23	
Center points mean	8.43	
Constant velocity	0.74	Significant
Temperature	0.51	Significant
Force	0.69	Significant
Power	−0.81	Significant
Time	0.04	
AB	−0.11	
AC	−0.14	
AD	0.36	
AE	−0.14	
BC	−0.16	
BD	0.54	Significant
BE	−0.31	
CD	−0.19	
CE	−0.69	Significant
DE	−0.19	

Standard error = 0.19

- The number of samples within each mean and S.D.
- The mean value and S.D. for each cell by cell name.

The bottom half of the sheet shows the data analysis. It includes a calculation of the main effects for each variable and the effects of their interactions. Main effects and interactions are calculated from the cell means. The standard error is calculated from the S.D.s of the cells. Each main effect and interaction is *t*-tested against the standard error to determine whether the effect is significant at a confidence level of 95%. The *t*-test is used to determine whether the effect is large enough to be real or whether it was due to random variation in the data.

In this experiment four of the variables had significant main effects on pull strength. They were constant velocity, temperature, force, and power. The first three had positive main effects signifying that higher levels increased the average pull strength. The fourth variable, ultrasonic power,

TABLE II

Factorial Interactions

Level of Temperature (B)

		Low Cell	Low Level (g)	Low Mean (g)	Center Cell	Center Level (g)	Center Mean (g)	High Cell	High Level (g)	High Mean (g)
Level of Power (D)	Low	E	8.50					B	7.70	
		A	7.90					ABE	8.70	
		C	9.00					BCE	8.60	
		ACE	9.20					ABC	9.50	
			34.60	8.65					34.50	8.63
	Center				C1	8.60				
					C2	8.10				
					C3	8.60				
						25.30	8.43			
	High	D	5.80					BDE	7.80	
		ADE	8.00					ABD	8.70	
		CDE	6.90					BCD	8.60	
		ACD	8.50					ABCDE	8.30	
			29.20	7.30					33.40	8.35

Interaction effect = (8.65 + 8.35 - 7.3 - 8.63) / 2 = 0.54.

Level of Force (C)

		Low Cell	Low Level (g)	Low Mean (g)	Center Cell	Center Level (g)	Center Mean (g)	High Cell	High Level (g)	High Mean (g)
Level of Time (E)	Low	A	7.90					C	9.00	
		B	7.70					ABC	9.50	
		D	5.80					ACD	8.50	
		ABD	8.70					BCD	8.60	
			30.10	7.53					35.60	8.90
	Center				C1	8.60				
					C2	8.10				
					C3	8.60				
						25.30	8.43			
	High	E	8.50					ACE	9.20	
		ABE	8.70					BCE	8.60	
		ADE	8.00					CDE	6.90	
		BDE	7.80					ABCDE	8.30	
			33.00	8.25					33.00	8.25

Interaction effect = (7.53 + 8.25 - 8.25 - 8.9) / 2 = −0.69

had a negative main effect, signifying that decreasing ultrasonic power had a positive effect on pull strength. Figure 4 is a plot of the pull strength main effect due to power. It shows that the average difference (the main effect), between the 8 cells that were run at high ultrasonic power and the 8 cells run at low, was −0.81 grams.

In addition to the main effects there were two significant interactions. Table II shows how the cells are sorted based on whether the interacting variables are at their high or low levels. By inspection of the means we select the best operating range. Based on the interactions one should avoid operating at either low temperature with high power or low force with low time.

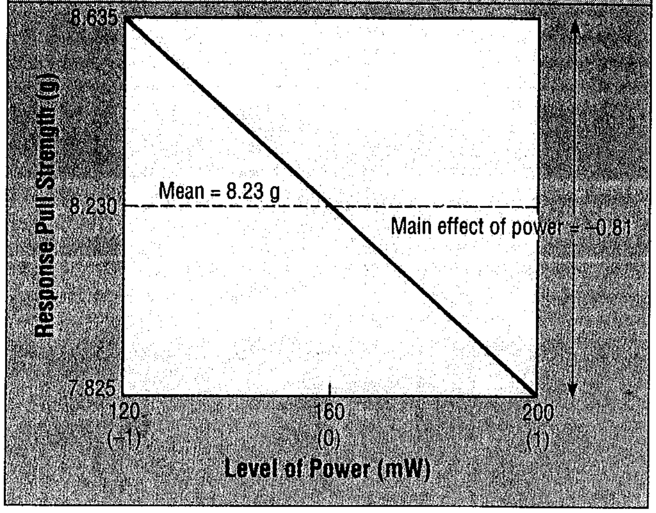
As a result of this experiment, the process was moved in the direction of the optimum: high constant velocity, high temperature, high force, and low ultrasonic power. Additional experiments were used to improve reliability and to further increase the average pull strength.

Part II of this article will review examples of the experiments used for the remaining three process situations. ■

References

1. T.N. Goh, "A Control Chart for Very High Yield Processes," *Quality Assurance*, vol. 13 (1), p. 18, March 1987.
2. G.E.P. Box, W.G. Hunter, J.S. Hunter, "Statistics for Experimenters," Wiley, New York, 1978.
3. *Ibid.*, chap. 12.
4. The K&S Template, along with a monograph entitled, "A Cookbook Recipe for Running a 2^{5-1} Fractional Factorial DOX," is available from Kulicke & Soffa Ind., Inc., 2101 Blair Mill Rd., Willow Grove, PA 19090, Attn: Mr. John Condit, Mgr., Tech. Information.

FIGURE 4



Pull strength main effect due to power.

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How to Optimize and Control the Wire Bonding Process: Part II

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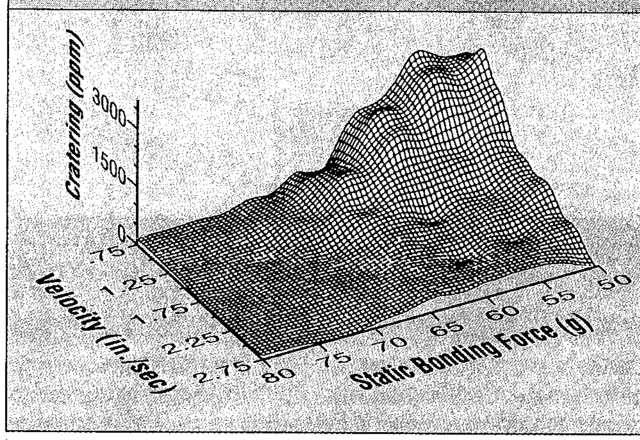
ABSTRACT

To help process engineers improve, optimize, and control the wire bonding process, proven statistical analysis tools/techniques are provided to deal with four stages of a process. Part I (*SST*, November 1990) covered development of a new process. Part II will discuss a process running at low yield, improving a marginally acceptable process, and maintaining process quality.

FIGURE 5



Cratering response surface [5].

Process Running at Low Yield

Where a process is running, but at unacceptable yields, response surface techniques are useful for improving and optimizing the process. The variation in process output, as adjustments are made, is called a response surface. Typical response surfaces are composed of data from measuring pull strength, shear strength, bond placement, cratering, loop straightness, etc. In semiconductor assembly the term "bond window" has been used to describe a response surface.

Figure 5 is a response surface plot for wirebond cratering [5]. It shows an optimum range of safe operating parameters which results in good bonding without cratering. The benefit of such plots is that they give a good graphic respresentation of the process and the interactions of several important variables, simultaneously. One type of response surface experiment, called the central composite design (CCD) has been used extensively by K&S for process development and optimization of results.

Central Composite Design (CCD)

The CCD experiment provides real optimization but it requires more samples for fewer variables than the fractional factorial designs discussed in Part I of this article. Figure 6 is a three-dimensional representation of a four variable CCD. Each axis or variable in this design has 5 levels ($-\alpha$, -1, 0, 1, α). Instead of running half the factorial points, all 16 (i.e., 2^4) are required. In addition there are 8 α points and 6 center points instead of the 3 in the fractional factorial. The location of the α points on each of the axes is dependent on the number of variables in the experiment. The distance is the square root of the number of variables. For the four variable experiment, the α points are at -2 and 2.

Table III shows the variables and levels for an experiment to measure the ball bond shear strength response surface for the K&S 1484XQ bonder. The unit change in force was 5 grams, thus the α points were ± 10 grams from the center of the range of forces studied. The benefits of this distribution of sampling levels is that the heavy center-weighting provides a good measure of repeatability and the α points are necessary for inclusion of quadratic and interaction terms.

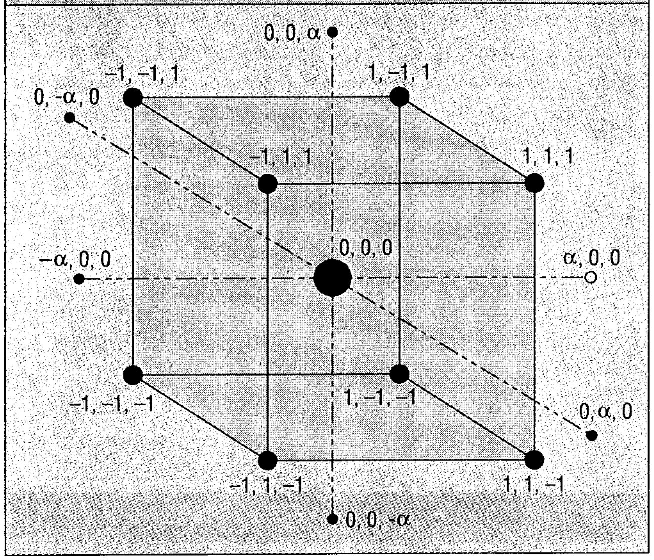
The analysis of CCD experiments is done using multiple regression methods [6]. Each response is regressed against a series of predictor variables that includes all of the main

TABLE III

Central Composite Design Variables and Levels for 1484XQ

Variable	Unit Δ	Level $-\alpha$	-1	0	1	α
Force (g)	5	25	30	35	40	45
Power (mw)	15	45	60	75	90	105
Temp. (°C)	25	150	175	200	225	250
Time (ms)	5	10	15	20	25	20

FIGURE 6



Central composite design for four independent variables.

TABLE IV

Central Composite Design Sample Data Sheet

Level of Variables Var 1	Var 2	Var 3	Var 4	Response
−1	−1	−1	−1	
1	−1	−1	−1	
−1	1	−1	−1	
1	1	−1	−1	
−1	−1	1	−1	
1	−1	1	−1	
−1	1	1	−1	
1	1	1	−1	
−1	−1	−1	1	
1	−1	−1	1	
−1	1	−1	1	
1	1	−1	1	
−1	−1	1	1	
1	−1	1	1	
−1	1	1	1	
1	1	1	1	
−2	0	0	0	
2	0	0	0	
0	−2	0	0	
0	2	0	0	
0	0	−2	0	
0	0	2	0	
0	0	0	−2	
0	0	0	2	
0	0	0	0	
0	0	0	0	
0	0	0	0	
0	0	0	0	
0	0	0	0	
0	0	0	0	

effects, interactions, and quadratic terms. Terms that are significant and should be included in the regression are tested using the excess sums of squares principle. Terms that are not significant are removed from the regression equations [6]. The authors have used the Minitab™ software, but many good regression analysis software packages are available. Once the initial working curves and response surface have been developed, additional tests should be used to provide confirmation and replication.

Running the Experiment

Table IV is a sample data sheet for the four factor CCD experiment. It includes the 16 factorial points, 8 α points and 6 center points required. The sample data sheet is shown in parametric form. Once variables are chosen and their levels selected, the parametric levels should be converted to actual levels. Again, the run sequence must be randomized. Non-random conditions require alternative experimental designs. As before, the experiment should be run as planned and the devices tested in the same order as the experiment sequence. Additional response measurements are acceptable, as long as the integrity of the devices is maintained.

Table V shows the regression analysis and an analysis of variance (ANOVA) of the 1484XQ experiment based on the variables and levels of Table III and the sampling plan of Table IV. The large value for the F-statistic (162.7) demonstrates the validity of the regression. Typically, values of F greater than 30 are sought for this type of analysis. The analysis of the regression equation showed that the average shear strength was 39.3 grams (constant term), all of the main effects were linear, and there were no significant interactions. The most significant variable was ultrasonic power (largest F-value for an individual term). To interpret the effect of ultrasonic power on shear strength in actual machine units (mW) the regression equation is used (Table V). It shows the coefficient of ultrasonic power (slope) is 6.8 grams/parametric unit. Dividing this by 15 mW/parametric unit (Table III) gives us an effect of 0.45 grams shear strength/mW.

Process Acceptable But Not Optimized

Process capability (C_p) is an important quantifier of a high quality process. The Western Electric Quality Handbook [7] defines process capability as the natural variation of a process after all of the unnatural, explainable disturbances have been eliminated and the process is operating in a state of statistical control. C_p has been defined mathematically [8] as:

$$C_p \; = \; \text{design tolerance} \, / \, 6 \text{ S.D.}$$

where design tolerance is the range over which the product can vary and yet remain acceptable.

TABLE V

1484XQ Ball Shear Strength

Predictor	Coeff	S.D.	t-ratio
Constant	39.3467	0.2722	144.55
Force	1.0958	0.3043	3.60
Power	6.7958	0.3043	22.33
Temperature	3.0625	0.3043	10.06
Time	1.8542	0.3043	6.09

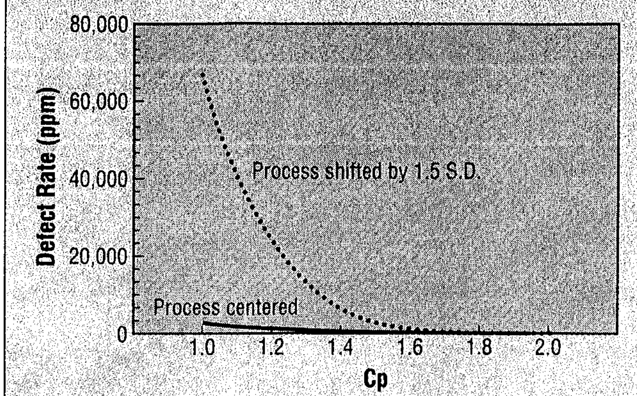
The regression equation is:
Shear = 39.3 + 1.10 Force + 6.80 Power
+ 3.06 Temperature + 1.85 Time.
s = 4.715

Analysis of Variance

Source	DF	SS	MS	F
Regression	4	14448.2	3612.1	162.71
Error	295	6557.7	22.2	
Total	299	21005.9		

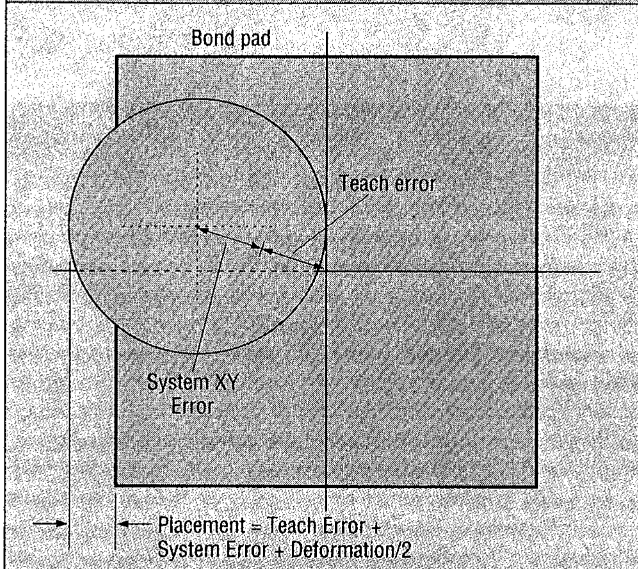
Source	DF	SEQ SS	MS	F
Force	1	288.2	288.2	12.98
Power	1	11084.0	11084.0	499.27
Temperature	1	2250.9	2250.9	101.39
Time	1	825.1	825.1	37.16

FIGURE 7



Effect of process shift on defect rate.

FIGURE 8



Bond placement accuracy model.

This definition illustrates the classic conflict between design specifications and manufacturing repeatability. The 6 S.D. spread is known as the manufacturing distribution and is a measure of the variation in the product actually produced. Even when $C_p = 1$, the process produces 2700 ppm defects since 6 S.D. does not include all variation possible.

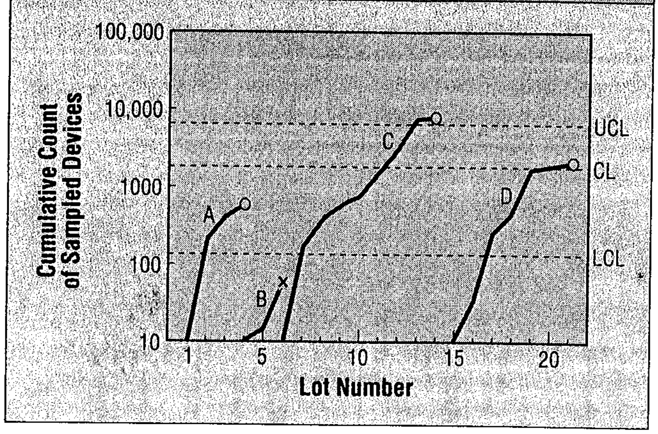
To make matters worse, if the process mean is not equal to the specification center, the defect rate can be much larger. Figure 7 shows the effect of a process shift on defect rate. A centered process operating at $C_p = 1$ produces 2700 ppm defects. Both the centered process and a process shifted by 1.5 S.D. have a $C_p = 1$ but the shifted process produces 25 times more defects or 6.7% scrap. The term C_{pk} describes the process capability of a process that has not been centered. For a noncentered process, the distance (in units of S.D.) from the process mean to the closest specification limit must be used to calculate the defect rate. The capability of targeting the process to the center of the specification is one of the benefits of design of experiment (DOX) and response surface methods.

The value of C_{pk} is a measure of process robustness. Increasing C_{pk} requires a continuous, iterative process, using successive DOX and response surface experiments to reduce the residual error. The results of each successive experiment are incorporated into the choice of variables, building a database of process knowledge. Process changes, design changes, and materials changes are all tested against the knowledge base, the goal being to reduce the residual error. The process is driven toward increased control and higher reliability. Improved yields are an automatic benefit.

Running the Process Capability Study

A process capability study is an experiment designed to measure normal variation. The most important ingredient, time, allows one to measure the process drift. A bond placement accuracy model based on a process capability study is described in Fig. 8. A series of factorial and central composite experiments provided the data and multiple regression and ANOVA software packages did the calculations necessary to attribute the total process variance to components that were used for the calculation of process capability [9]. By running a series of experiments over an extended period of time, it was found that operator teach error contributed 50 percent of the total bond placement error on a typical automatic wirebonder. This information led to an important development in the pattern recognition system—Automatic Bondpad Centering (Pat. Pend.). With this feature the bonder automatically locates the center of the bond pad or lead during the teach cycle, thus eliminating the operator teach error and reducing the total bond placement error.

FIGURE 9



Cumulative production control chart.

Maintenance of Process Quality

Once a process is well understood and producing quality product at low defect rates, it must be monitored and controlled. Normal probability (*p*) control charts are not very useful for controlling processes with defect rates substantially below 1 percent. At low defect rates the distribution of defects becomes binominal. A single occurance switches the chart from a state of control to out-of-control.

In 1987, T.N. Goh [1] proposed a new method for using control charts with very high yield processes. The chart uses cumulative sample quantities between defects to set upper and lower control limits. The control limits for normal control charts are set using small sample lot sizes. The cumulative sample control chart uses both the average defect rate and the size of the inspection sample lot to set the chart control limits. The benefit of using control charts is that decision making is enhanced. Control charts tell us when to shut down the process for corrective action and when to start to be concerned about the process drift. Using control charts we are warned of potential problems before they are allowed to cause defective product. Another benefit is that control charts also tell us when the process is performing much better than expected. A close analysis of what makes a process perform better than usual often leads to really significant improvements in overall process quality.

The defects detected during the long time periods associated with control chart maintainence are recorded and analyzed by Pareto charts [10]. Pareto charts are frequency distributions of the defects by category. Highest priority is given to finding the root causes of those defects that occur most frequently. By focusing engineering efforts on the most important causes of defects, Pareto charts help to quickly drive the process toward yield improvements.

Figure 9 is a control chart taken from Goh for a process operating at a 400 ppm defect rate with an in-process sampling plan of 200 pieces per lot. Production sampling starts and accumulates on line A. Lots change and the process continues to operate until a defect is generated after 750 devices have been sampled. However, the defect data point is above the lower control limit so the process is still in control. The cumulative count is now reset to zero and the normal lot sampling plan resumes. At device 56 on line B another defect occurs. This time the process is out of control. The defect is examined, a solution determined, and the process begins again at cumulative count zero. No defects occur on line C until device 7800. This exceeds the upper control limit and should provoke analysis. Once again the cumulative count is set to zero. On line D it reaches 1500 before a defect occurs and the process determined to be still in control.

Conclusion

A combination of methods including response surface procedures, design of experiments, process capability studies, and control charts for high yield processes provide the best overall approach for optimizing and controlling wire-bonding. The first three give insight into the sources of process variation and long term process stability, while control charting and then Pareto analysis provide the tools for monitoring the process to ensure excellent yields. ■

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Editor's note: For prior references, figures, tables, and authors' biographies, see Part I, *SST*, November 1990.