Design of Experimentation for Affordability

Affordability is not exactly the primary word which comes to mind when discussing the use of design of experiments (DOE) principles, but is generally accepted as a necessary part of the engineering activities required in the development of a product or process. However, a number of studies have indicated that the cost savings derived from a well deliberated experimental design can be substantial in the initial stages where the conditions or parameters of a process are determined. Some studies have shown a greater than 50% cost savings compared to the more conventional means of trial and error approaches to process development. At ACI Technologies (ACI), we have found the use of DOE techniques fundamental in eliminating extraneous costs otherwise spent on unnecessary testing.

Case Study

Recently a project was undertaken at ACI to qualify a surface mount technology (SMT) process to meet the IPC Class 3 qualifications for solder wetting, ionic cleanliness, and visible flux residue. The contract manufacturer had introduced a new SMT solder process that subsequently exhibited electrical failures after production of the first articles. The following is an anatomy of the investigation and experimental process used to determine the acceptable process parameters.

1. Failure Summary

The preliminary investigations that led to this study revealed that the first articles produced by the contract manufacture had evidence of the following:

- Electrical failure after biased highly accelerated stress test (HAST) testing due to electromigration causing corrosion.
- Unacceptable amounts of voiding in the BGA devices.
- Occasionally, severe cases of solder de-wetting on surface pads.

2. Causes - Brainstorming Session

Through this experiment, it was determined that 10 factors (Table 1) in the SMT process could possibly account for the various failures that were identified. If two term interactions are taken into consideration, the amount of experimental runs would exceed 1000; a very costly and time consuming experiment. When so many combinations and iterations are involved, it is critical to choose a good software program that will evaluate the probability of detecting variability on the basis of the factors and interactions chosen for the experiment. This will allow you a minimum amount of experimental runs to maintain a statistically valid experiment. It is important to note that decreasing the number of experimental runs will decrease your probability of detecting a response, as you increase the number of factors and interactions. Therefore, it is important to choose a program that gives you the flexibility to design an experiment around the interactions and main effects most likely to affect the process or product quality.

Factors				
Name	Role	Values		
Belt Speed	Continuous	1		3
Peak Temperature	Continuous	230		260
Ramp Rate	Continuous	5		20
Cool Rate	Continuous	1		3
Paste	Categorical	X		Y
Surface Finish	Categorical	Tin	OSP	Gold
Solder Volume	Continuous	2		6
Cleaner Temperature	Continuous	40		75
Cleaner Concentration	Continuous	5		20
Cleaner Type	Categorical	Aqueous		Semi-Aqueous

Table 1: Factorial Values.

3. Type of Designs

There are a number of experimental design variations that can be tailored specifically to the type of data that is required.

A *D-Optimal Design* (Figure 1A) places the majority of its experimental runs at the extremes (70-80%), with a few in the center regions. This

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model is appropriate for screening designs where a bolder approach in assigning factorial levels may be warranted. The average variance, relative to error, would be lower on the extremes, but this model would be inappropriate for quadratic effects.

The *I-Optimal Design* (Figure 1B) minimizes the average variance prediction within the interior regions of the experiment, making it more appropriate for Response Surface Designs. Most of its runs are located in the inner regions of the design space, making it better to predict responses in the inner region.

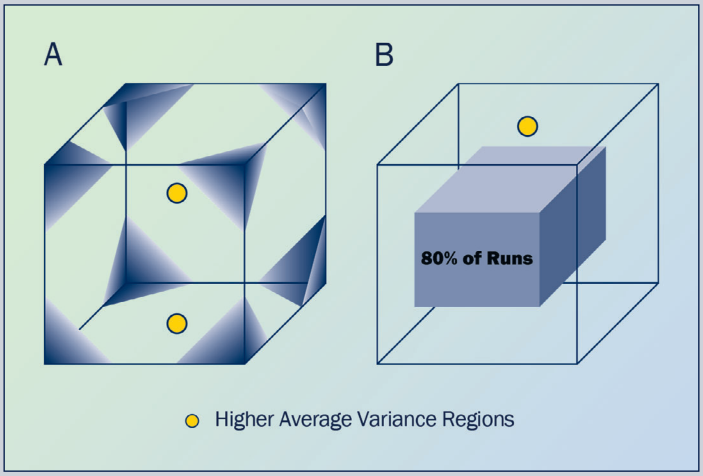

Figure 1: A shows D-Optimal Design. B depicts I-Optimal Design.

4. Choosing Factorial Values

The number of factors involved in the DOE can be either categorical or continuous in nature. If conducting a screening experiment, the continuous variables should be assigned values which represent the reasonable extremities of the process parameters. It is always easier to interpolate predictive responses than to extrapolate, where quadratic or cubic effects are not taken into account.

5. Responses

The three response variables for this experiment were wetting, cleanliness, and flux residue. The responses were numerically assigned a number from one through 10, determined through a combination of visual inspection and ionographic testing. It may be beneficial at times to assign a numerical value to a categorical response to obtain the necessary statistical data to determine variability. In the case of this experiment, a numerical metric was easily adaptable. The value of one indicated the worst case response, with the value of 10 indicating the best response. For example, the best wetting, the cleanest assembly, and the least amount of residue all had values of 10.

6. Interpreting the Model Data

Assuming a general linear model is used, there are two important statistical tables to consider. The summary of fit and analysis of variance (Table 2) will present the statistical relevance of the experimental model based on the particular response variable and factors used in the DOE. In this example the wetting response was used.

The three key areas to look at are:

- *F-Ratio 14.693*. Which indicates the wetting response produced a high signal to baseline noise.
- *Prob<.0001*. Which indicates a very strong probability that the wetting responses were not random in nature.
- *R-Square adj*. In this case, the 0.909 indicates that 90% of all the variance around the means is accounted for within the model.

Essentially, the model showed a very strong response in wetting for the assigned factorial values.

Summary of Fit	
RSquare	0.975486
RSquare Adj	0.909096
Root Mean Square Error	0.535099
Mean of Response	7.268889
Observation (or Sum Wgts)	90

Analysis of Variance				
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	65	273.46094	4.20709	14.6931
Error	24	6.87195	0.28633	Prob > F
C. Total	89	280.33289		< .0001

Table 2: Wetting Response.

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7. Interpreting Factorial Data

Using similar metrics to the model, it was determined that the greatest wetting response was produced by changing the peak temperature, followed by the ramp rate. The interaction between Peak Reflow Temperature and Surface Finish (Figure 2) also had a significant response. For this customer's particular assembly, an electroless nickel immersion gold (ENIG) finish at a higher process temperature improved wetting to the surface pads.

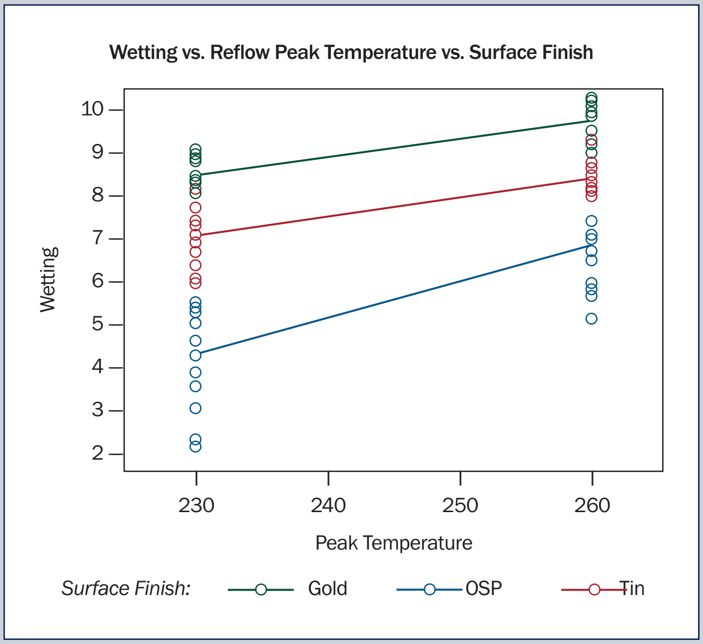

Figure 2: Surface Finish vs. Peak Temperature.

8. Conclusion

There were other elements to this experiment, but for the purpose of this article, it suffices to show that with the use of DOE techniques, the engineers at ACI were able to determine the proper process conditions for a valued customer. This enabled them to save time and money on their product development.

ACI conducts training classes on various aspects of DOE, design for manufacturability (DFM), and statistical process control (SPC). For more information, please contact the Registrar at 610.362.1295, via email to registrar@aciusa.org or visit the website at www.aciusa.org.

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