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## **Surface Mount Technology Process Optimization**

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## ABSTRACT

One of the objectives in conducting this work is to develop a process optimization for manufacturing. Screen printing is the first and one of the most critical process steps in a printed circuit board assembling manufacturing. Solder paste volume on each pad has a direct effect on the product quality and reliability. This experiment concentrates on solder paste volumes obtained on fine pitch pad geometry's. Pads with this geometry have a 0.020" pitch between lead centers. The key is to have just the right volume deposited in the pad. Too little will cause a faulty joint or an unreliable joint with an electrical continuity failure potential. On the other hand, too much will create solder short problems or worse yet, solder balls. Solder balls can become detached after the product has been tested, causing potential field failures. A  $2^4$  factorial design has been considered in order to optimize the process.

Keywords: Surface Mount Technology, Process Optimization, Robust Design, Design of Experiments

## 1. INTRODUCTION

In any factory where a printed board is assembled using Surface Mount Technology (SMT), the first process step is usually screen printing. The screen printing process is the step where solder in the form of paste, is deposited to the different pad images on the printed circuit board (PCB). SMT components are eventually placed on these pads with solder paste. The solder paste is spread onto a stainless steel stencil with apertures that follows the design of the PCB being processed. The objective is to accurately force the correct amount of solder paste, through this stencil orifices, onto the PCB pads. PCBs that have been processed through screen printing, will proceed to the next process step, usually component placement. The SMT components are placed on top of the previously deposited solder paste. One of the solder paste characteristics, "tackiness," will play an important role at this point. It will hold the components in place until it reaches the reflow process. At this point the flux, which is one of the solder paste most important components, will heat up and start the activation process. This activation process is necessary to clean up the surfaces (PCB pads and component termination's), usually from oxidation or other contaminants. With the correct oven profile, a properly formed solder joint will emerge from this process. This will provide for the necessary mechanical attachment strength and electrical continuity between the component and the PCB circuits.

Factor	Level Setting
$X_1 => Print Speed$	+
$X_2 \Rightarrow Snap Off$	+
X <sub>3</sub> => Squeegee Angle	
X <sub>4</sub> => Stencil Wipe	-

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Through regression analysis, it was proven that the one half resolutions IV approach models the Full Factorial Experiment with only half of the treatment runs. All of the main effects that are significant are predicted by this model. However, the aliases, caused some of the interactions not to be considered as significant.

The regression model for the Full Factorial Experiment is:  $Y^{=} 1470.5+(7.816) \times 1+(4.016) \times 2-(38.684) \times 4-(6.688) \times 1\times 3-(4.938) \times 2\times 4+(6.275) \times 3\times 4+(3.366) \times 1\times 2\times 3$ 

While the regression model for the One Half Fraction Resolution IV is: y^=1472.8+(10.850) x1+(2.300)x2-(42.050)x4+(9.188)x1x2-(11.625)x1x3

Both models are similar, especially on the main factors. We loose some visibility when it comes to the interactions. This is due to the aliasing effects.

## 2- PROCESS SETUP AND DESIGN

Through the use of the Taguchi's optimization process, it was concluded that the optimum response was obtained with factors at the following level setting:

Factor	Level Setting
$X_1 \Rightarrow Print Speed$	+
$X_2 \Rightarrow Snap Off$	+
X <sub>3</sub> => Squeegee Angle	e Any angle
X <sub>4</sub> => Stencil Wipe	-

Taguchi's approach in this case yielded almost identical results than the full factorial experiment. One advantage in using the Taguchi's optimization process is that it required far less calculations and did not require the use of any statistical software. However, it should not be concluded that this will be the case for all experimental designs.

This experiment studies the effect of four factors on a screen printing process. These factors were varied at two levels each as part of a  $2^4$  full factorial design.

Factor	Level	
Print Speed	-	+
Snap Off Gap	30mm/sec	25mm/sec
Squeegee Angle	0.5 mm	1.00 mm
Stencil Clean Frequency	5 min	10 min

Other variables that will not change during this experiment are shown in Table 1 below.

### Table 1: Other variables that will remain fixed:

Squeegee Type:	Metal	
Stencil Thickness:	6 mils	
Solder Paste:	Indium	
Equipment:	Dek288	
Conveyor:	Clamping	
Firmware:	3.0	
Fiducial Type:	Round (1.9mm)	
Cleaning Solution:	Alcohol	
Cleaning Material:	Paper Wipe	
Operator:	Experienced	
Unit Under Test:	TalkAbout PCB	
Paste on Stencil Volume:	Normal – Heavy	
Paste Kneading:	None	
Paste warm-up Period:	24 Hours	
Paste Lot Usage:	FIFO	

Several consideration were taken during data collection. The solder paste volume was measured on 12 of the 64 total PCB pads for one of the most critical parts. The pins were randomly selected to avoid any possibility of biased. The response was measured as the average on all 12 pins by using the system's own vision system which is capable of measuring volume deposits. To test the repeatability of the measurements, a panel was printed and measured over a weeks time frame. ANOVA was used to detect any statistical significant difference between the means of the different days.

## **3 FULL FACTORIAL 2<sup>4</sup> DESIGN**

This type of experiment design is extensively used, especially if it is of interest to study the interaction effects of factors in the response. In this experiment, the factors are fixed, the treatments and runs were randomized and the usual normality assumptions were satisfied.

Factors->	X1	X2	X3	X4
Run Label	Print	Snap Off	Squeegee	Stencil
	Speed	Gap	Angle	Wipe
(1)	-1	-1	-1	-1
А	+1	-1	-1	-1
В	-1	+1	-1	-1
Ab	+1	+1	-1	-1
С	-1	-1	+1	-1
Ac	+1	-1	+1	-1
Bc	-1	+1	+1	-1
abc	+1	+1	+1	-1
D	-1	-1	-1	+1
Ad	+1	-1	-1	+1
Bd	-1	+1	-1	+1
abd	+1	+1	-1	+1
Cd	-1	-1	+1	+1
acd	+1	-1	+1	+1
bcd	-1	+1	+1	+1
abcd	+1	+1	+1	+1

## 3.1 Full Factorial Treatment Runs and Responses Matrix

Avera				
Run 1	Run 2	Run 3	Run 4	Totals
1500.2	1496.7	1495.3	1500.6	5992.8
1502.4	1501.1	1496.2	1502.0	6001.7
1509.3	1504.1	1505.8	1506.1	6025.3
1548.8	1550.1	1551.3	1550.1	6200.3
1498.8	1497.6	1500.3	1497.7	5994.3
1502.6	1504.4	1503.1	1504.4	6014.5

1504.8 1512.7 1503.7 1508.8 6030.0   1508.0 1509.1 1508.8 1508.6 6034.4   1416.2 1377.6 1420.4 1425.8 5640.0   1438.4 1441.8 1438.8 1443.7 5762.7   1418.9 1382.8 1389.0 1419.9 5610.7   1437.7 1443.3 1438.6 1448.5 5768.1   1442.2 1434.4 1436.0 1443.4 5758.0   1441.1 1443.3 1437.8 1440.8 5762.9   1431.4 1443.3 1440.0 1439.9 5754.6   1436.8 1441.1 1442.2 1440.8 5760.9					
1416.2 1377.6 1420.4 1425.8 5640.0   1438.4 1441.8 1438.8 1443.7 5762.7   1418.9 1382.8 1389.0 1419.9 5610.7   1437.7 1443.3 1438.6 1448.5 5768.1   1442.2 1434.4 1436.0 1443.4 5758.0   1441.1 1443.3 1437.8 1440.8 5762.9   1431.4 1443.3 1440.0 1439.9 5754.6   1436.8 1441.1 1442.2 1440.8 5760.9	1504.8	1512.7	1503.7	1508.8	6030.0
1438.4 1441.8 1438.8 1443.7 5762.7   1418.9 1382.8 1389.0 1419.9 5610.7   1437.7 1443.3 1438.6 1448.5 5768.1   1442.2 1434.4 1436.0 1443.4 5758.0   1441.1 1443.3 1437.8 1440.8 5762.9   1431.4 1443.3 1440.0 1439.9 5754.6   1436.8 1441.1 1442.2 1440.8 5760.9	1508.0	1509.1	1508.8	1508.6	6034.4
1418.9 1382.8 1389.0 1419.9 5610.7   1437.7 1443.3 1438.6 1448.5 5768.1   1442.2 1434.4 1436.0 1443.4 5758.0   1441.1 1443.3 1437.8 1440.8 5762.9   1431.4 1443.3 1440.0 1439.9 5754.6   1436.8 1441.1 1442.2 1440.8 5760.9	1416.2	1377.6	1420.4	1425.8	5640.0
1437.71443.31438.61448.55768.11442.21434.41436.01443.45758.01441.11443.31437.81440.85762.91431.41443.31440.01439.95754.61436.81441.11442.21440.85760.9	1438.4	1441.8	1438.8	1443.7	5762.7
1442.21434.41436.01443.45758.01441.11443.31437.81440.85762.91431.41443.31440.01439.95754.61436.81441.11442.21440.85760.9	1418.9	1382.8	1389.0	1419.9	5610.7
1441.1 1443.3 1437.8 1440.8 5762.9   1431.4 1443.3 1440.0 1439.9 5754.6   1436.8 1441.1 1442.2 1440.8 5760.9	1437.7	1443.3	1438.6	1448.5	5768.1
1431.4 1443.3 1440.0 1439.9 5754.6   1436.8 1441.1 1442.2 1440.8 5760.9	1442.2	1434.4	1436.0	1443.4	5758.0
1436.8 1441.1 1442.2 1440.8 5760.9	1441.1	1443.3	1437.8	1440.8	5762.9
	1431.4	1443.3	1440.0	1439.9	5754.6
Total: 94111.3	1436.8	1441.1	1442.2	1440.8	5760.9
Totali				Total:	94111.3

# **3.2** Sample size Choice Calculations:

Using the equation:

 $\Phi^2 = n\Sigma \tau_i^2 / a\sigma^2$ 

Ν	$\Phi^2$	Φ	a(n- 1)	Ξ	Powe r (1-∃)
2	2.9 9	1.73	16	0.4	0.6
3	4.4 9	2.1 2	24	0.0 8	0.92
4	5.9 9	2.4 4	32	0.0 1	0.99

In determining if a factor has a significant effect, we compare to  $F_{crit} = F_{0.05,1,48} = 4.04$ . From the ANOVA shown below, factors X<sub>1</sub>, X<sub>2</sub>, and X<sub>4</sub> are considered to be significant. The interactions with significance are identified in a similar manner.

Source of Variation	F Sig of F	
X1	62.83 .000	
X2	16.59 .000	
X3	2.96 .092	
X4	1539.27	.000
X1 BY X2	8.73 .005	
X1 BY X3	46.00 .000	
X1 BY X4	1.72 .196	
X2 BY X3	6.21 .016	
X2 BY X4	25.08 .000	
X3 BY X4	40.50 .000	
X1 BY X2 BY X3	11.65 .001	
X1 BY X2 BY X4	3.28 .077	
X1 BY X3 BY X4	3.03 .008	
X2 BY X3 BY X4	9.47 .003	
X1 BY X2 BY X3 BY X4	5.53	.023
Error	118.86 .000	
(Model)		

(Total)

R-Square = .974 Adjusted R-Squared = .966

## 3.3 Prediction Model

With SPSS, the coefficients for the significant effects are calculated as part of the model design.  $\beta o$  is estimated by averaging the total results.

The effects of the below factors was provided by SPSS. Shown here are factors and interactions with the most significant effect.

Variable	βι
X1	7.816
X2	4.016
X4	-38.684
X1*X3	-6.688
X2*X4	4.938
X3*X4	6.275
X1*X2*X3	3.366

Prediction Model (Full Factorial Design):

 $y^{*} = \beta o + \beta_{1}x_{1} + \beta_{2}x_{2} + \beta_{3}x_{4} + \beta_{4}x_{1}x_{3} + \beta_{5}x_{2}x_{4} + \beta_{6}x_{3}x_{4} + \beta_{7}x_{1}x_{2}x_{3}$  $y^{*} = 1470.5 + (7.816)x_{1} + (4.016)x_{2} - (38.684)x_{4} - (6.688)x_{1}x_{3} + (4.938)x_{2}x_{4} + (6.275)x_{3}x_{4} + (3.366)x_{1}x_{2}x_{3}$ 

In the full factorial experiment, all four factors had an effect based on hypothesis testing. However, Print Speed, Snap Off Gap and Stencil Wipe had the most and Squeegee Angle was just marginally significant. All of the interactions had some effects, but only four of the eleven interactions had a significantly higher effect.

The One Half Fraction Design becomes a helpful analysis method, especially when the number of fractions in a  $2^{K}$  experiment design is high. As an example a  $2^{6}$  design requires 64 runs, assuming that only one replicate is needed. In most cases, up to three replicates are usually required, bringing this total to an amazing 192 runs. It becomes obvious that the design rapidly outgrows the resources of most experimenters.

This experiment was analyzed through the use of a One Half Fraction Resolution IV  $2_{IV}^{4-1}$  Design. It will be demonstrated that the predicted responses will be similar to the full factorial design. The advantage is that only half of the runs are required. This helps maximize the resources. A prediction model will be developed and compared to the full factorial model shown previously.

This design is presented below:

## 3.3.1 Fractional Fractorial Treatment Runs and Response Matrix

Factors->	X1	$X_2$	X <sub>3</sub>	$X_4$
Run	Print	Snap Off	Squeegee	Stencil
	Speed	Gap	Angle	Wipe
(1)	-1	-1	-1	-1
ad	+1	-1	-1	+1
bd	-1	+1	-1	+1
ab	+1	+1	-1	-1
cd	-1	-1	+1	+1
ac	+1	-1	+1	-1
bc	-1	+1	+1	-1
abcd	+1	+1	+1	+1

Average So	Average Solder Paste Volume (mils <sup>3</sup> )				
Run 1	Run 2	Run 3	Run 4		
1500.2	1496.7	1495.3	1500.6		
1438.4	1441.8	1438.8	1443.7		
1418.9	1382.8	1389.0	1419.9		
1548.8	1550.1	1551.3	1550.1		
1444.2	1434.4	1436.0	1443.4		
1502.6	1504.4	1503.1	1504.4		
1504.8	1512.7	1503.7	1508.8		
1436.8	1441.1	1442.2	1440.8		

#### 3.3.2 Analysis of Variance for this One Half Fraction Resolution IV Design

#### Analysis of Variance - Fractional Factorial Resolution IV Design

Fractional Factorial ANOVA results Tests of Significance for RESPONSE using UNIQUE sums of squares

SOV	F	Sig of F
X1	68	0
X2	3.06	0.093
X3	0	0.948
X4	1021.41	0
X1 BY X2	48.76	0
X1 BY X3	78.06	0
X1 BY X4	0.78	0.386
Error		
(Model) 67587.	99 7 9655.43	174.3 0

(Model) 67587.99 7 9655.43 174.3 (Total) 68917.51 31 2223.15 R-Squared= 0.981 Adjustly R-Squared= 0.975

### 3.3.3 Prediction Model

The effects of the below factors was provided by SPSS. Shown below are factors and interactions with the most significant effect. Although the ANOVA results shows significant effects for most factors and interactions except for Factor  $X_3$  and interaction  $X_1*X_4$ , I selected those with the greatest impact.

Variable	<u>∃i</u>
X1	10.850
X2	2.300
X4	-42.050
X1*X2	9.188
X1*X3	-11.625

Prediction Model (One Half Fraction Design)  $y^{*} = \beta o + \beta_{1}x_{1} + \beta_{2}x_{2} + \beta_{3}x_{4}$  $+ \beta_{4}x_{1}x_{2} + \beta_{5}x_{1}x_{3}$ 

 $y^{=} 1472.8 + (10.850)x_1 + (2.300)x_2 - (42.050)x_4 + (9.188)x_1x_2 - (11.625)x_1x_3$ 

This is very close to the prediction model obtained in the Full Factorial experiment. It is conveniently shown below.

Prediction Model (Full Factorial Design):  $y^{*} = \beta o + \beta_{1}x_{1} + \beta_{2}x_{2} + \beta_{3}x_{4} + \beta_{4}x_{1}x_{3}$  $+ \beta 5x_{2}x_{4} + \beta_{6}x_{3}x_{4} + \beta_{7}x_{1}x_{2}x_{3}$ 

 $y^{=} 1470.5 + (7.816)x_1 + (4.016)x_2 - (38.684)x_4 - (6.688)x_1x_3 + (4.938)x_2x_4 + (6.275)x_3x_4 + (3.366)x_1x_2x_3$ 

## 4- PROCESS OPTIMIZATION

An orthogonal array is consulted to determine a subset of the full factorial that can be used in this process optimization method. In essence, a response average as well as a Signal to Noise ratio (S/N) is calculated. The equation used to calculate the S/N ratio needs to be selected by the experimenter, depending on these three categories: "Large is better," Smaller is better" or "Nominal is better". In the case of this experiment, before any of the runs were executed, the preference for a S/N ratios was "Nominal is better". After looking at the results, it was noticed that most of the response resulted to be lower than the preferred volume paste. The S/N ratio calculation equation was quickly switched to "Larger is better". The S/N ratio is a measure of the response reference to the amount of variability in the response. A higher S/N ratio is indicative of lower process variability. Response tables are then constructed for the average value and S/N ratio as demonstrated in the classroom. The differences in each of the treatment levels are calculated and the those with the highest difference are determined to be significant. The significant treatments are then chosen from these tables based on the best response. For factors that do not have an effect on the response, either level is chosen. Usually it is up to the experimenter to select this "Don't Care" factor levels based cycle time or cost reduction.

Factors->	X1	$X_2$	X3	$X_4$
	Print	Snap Off	Squeegee	Stencil
Run	Speed	Gap	Angle	Wipe
1	-1	-1	-1	-1
2	+1	-1 -1		+1
3	-1	+1	-1	+1
4	+1	+1 +1 -1		-1
5	-1	-1	+1	+1
6	+1	-1	+1	-1
7	-1	+1	+1	-1
8	+1	+1	+	+1

### **Taguchi's Optimization**

Ybar	Sm	Ve	S/N
1498.2	2244599	6.721	63.51
1440.7	2075520	6.366	63.17
1402.7	1967474	380.588	62.94
1550.1	2402758	1.042	63.81
1439.5	2072160	25.069	63.16
1503.6	2260888	0.877	63.54
1507.5	2272556	16.759	63.57
1440.2	2074260	5.460	63.17

#### **Response Tables:**

Response Table (S/N)

Level	X1	$X_2$	X <sub>3</sub>	$X_4$
-1	63.29	63.35	63.36	63.61
+1	63.42	63.37	63.36	63.11
Delta	0.13	0.02	0.00	0.50
Rank	2	3	4	1

Response Table (Ybar)

Level	$X_1$	$X_2$	X3	$X_4$
-1	1462.0	1470.5	1472.9	1514.9
+1	1483.7	1475.1	1472.7	1430.8
Delta	21.68	4.62	0.19	84.09
Rank	2	3	4	1

\*\* Note: Most of the responses were under 1536 mil<sup>3</sup> (Ideal Solder Paste Volume) Based on this fact, the S/NL ratio for Larger is Better was selected.

#### **Two Step Optimization**

Factor	Affect S/N	Affect Ybar	Affect S/N	Affect S/N & Ybar	Affect Ybar	Affect Neither
А	#	#		X <sub>1</sub>		
В	#	#		$X_2$		
С						X <sub>3x</sub>
D	#	#		X4-		

Conclusion from Tagushi Optimization:

Optimum response is obtained when running at the following levels: X1+X2+X3+X4

### 6. CONCLUSIONS

The screen printing process is a complex process. The number of variables that can have an effect on the response is large. Determining which factors are statistically significant by inspection alone is impossible. It is one processes like these where the use of experimental design is a must, especially when the ever lasting search for excellence is desired.

The full factorial ANOVA is one of the best tools to use if all of the factors and interactions are of interest. This of course is taking into consideration the economical and time aspects to execute all the treatment runs with replicates. A one half fraction design is acceptable if it is known that higher order interactions are not of concern. The Taguchi technique was the most powerful for this particular experiment. The significant effects were determined with only half of the runs needed on a full factorial and another advantage is that you do not require the use of any statistical software to get the optimal factor levels.

## 7- REFERENCES

<u>Kotlowitz, R.W.</u><sup>1</sup>; <u>Falaki, H.R.</u>:"Robust assembly technology for surface mount leadless ceramic components on organic circuit boards deployed in an outside-plant wireless base-station system". *Proceedings 2000 International Symposium on Microelectronics (SPIE Vol.4339)*, 160-5, 18-20 Sept. 2000, Boston, MA, USA

<u>Meller, Andy</u><sup>1</sup> :"Pin-in-paste technology: A durable, cost-saving connector solution". *ECN Electronic Component News*, v 52, n 5, p 13-15, May 2008.

Phlenz, M.H.:"Taguchi experiment to design for low cost, high reliability surface mounted components." *Combined Proceedings of the 1990 and 1991 Leesburg Workshops on Reliability and Maintainability Computer-Aided Engineering in Concurrent Engineering*, 153-60, 1992

<u>Bjorndahl, William D.; Selk, Ken; Chen, Wennei</u>: "Surface mount technology - capabilities and requirements." *IEEE Aerospace Applications Conference Proceedings*, v 4, p 285-291, 1997

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