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Research Article

Integrating the TRIZ and Taguchi's Method in the Optimization of Processes Parameters for SMT

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SMT is an assembly technology for core circuit board parts. Unless process parameters are effectively controlled, poor solderability may result in a decline in product quality. This study looks at an SMT manufacturing process in a multinational company. First, the TRIZ contradiction matrix is revised to investigate the association between the 39 parameters in the contradiction matrix and 13 parameters that influence the unevenness of solder paste in the solder paste printing process. Expert verification is then used to screen the key factors affecting the quality of SMT, which are then combined with Taguchi's method to identify the optimal parameter set influencing the thickness of SMT solder paste. *Results*. TRIZ identifies squeegee pressure, ejection speed, squeegee speed, and squeegee angle as the four parameters with the greatest influence on SMT solder paste thickness. Taguchi's method is used to identify the optimum levels set for the experimental factors and carry out confirmation experiments. The *S/N* ratio improved from 21.732 db to 26.632 db, while the mean also improved from the current 0.163 mm to 0.155 mm, close to the target value of 0.15 mm. The results show that applying TRIZ and Taguchi's method for the purpose of product improvement is feasible.

1. Introduction

Today, product cycles are short and undergo rapid changes. Consumer electronic products, such as smart phones, notebook computers, and digital cameras, play an important role in our everyday lives. As consumers become more demanding, there is an increasing emphasis on lighter, thinner, high quality, and low-priced products that can be delivered to the consumer quickly. In addition, due to global competition, businesses are increasingly demanding rigorous quality standards to meet customer's demand [1, 2].

To meet the demand for light, thin, short, and small electronic products, print circuit boards (PCB) have evolved from single-layer to multilayer boards, with a consequent reduction in their size. As a result, most traditional plated-through hole parts are gradually falling out of use. An effective solution to this is to attach electronic components onto the PCB, resulting in the development of surface mount technology (SMT). However, unless process parameters are effectively controlled, poor solderability may result in a decline in product quality. For example, if insufficient solder paste is deposited at the PCB printing stage, the strength of the solder joints may be inadequate or an empty solder phenomenon may occur. However, if too much solder paste is deposited, bridges may form between the solder joints, leading to short circuits.

Yang et al. [3] point out that SMT has become the primary tool for PCB assembly. An SMT quality problem may cause a significant production loss, and SMT quality issues are crucial to competition between companies. In the research on optimizing stencil printing, Tsai [4] offers a comparative perspective, finding that in the SMT manufacturing process 60% of stencil quality issues are caused by defects in solder paste printing. In their research using Taguchi's method to improve the parameters of solder paste printer processes, Lai and Wang [5] use optimized printing parameters, leading to an improvement of approximately 20% in solder paste printing quality. Recent studies on solder paste printing quality by Tsai [4] and Lai and Wang [5] have both produced significant improvements in solder paste printing quality.

Worsening feature / Improving feature		1			7		39
		Weight of moving object	...	...	Volume of moving object	...	Productivity
4	Length of nonmoving object				↓		↓
5	Area of moving object	→	→	→	4, 7, 14, 17		↓
...							↓
39	Productivity	→	→	→	→	→	—

Source: http://www.innovation-triz.com/TRIZ40/

Figure 1: An example of the contradiction matrix.

However, they fail to explain how they selected their experimental variables. Many researchers, including Yildiz [6, 7], Durgun and Yildiz [8], and Yildiz and Solanki [9], have applied Taguchi's method or algorithms to plan experiments and parameter optimization in the past few years.

Andersen and Fagerhaug [10] argue that the TRIZ contradiction matrix is a tool for eliminating root causes of problems in the engineering process and can be used to identify engineering parameters that cause engineering problems or conflicts. This study randomly selected 30 sets of data from the process-site and measured and calculated the process capability index as $C_{pk} = 1.24$. This figure does not meet Kane's [11] recommended minimum acceptable process capability index of $C_{pk} \geqq 1.33$, showing that there is still significant room for improvement in the quality of the solder paste printing process. Therefore, this study attempts to combine TRIZ and Taguchi's method to carry out empirical research. It is hoped that a predictive model of the manufacturing process outcomes can be used to identify optimized process parameters.

2. Literature Review

2.1. TRIZ. TRIZ is an abbreviation for the "theory of inventive problem solving" in the Russian language. The theory was developed by the Soviet inventor Altshuller [12] in 1946 with the aim of solving different types of contradictions.

Altshuller [12] developed the concept of the "technical contradiction" after observing a large number of invention proposals. The technical contradiction arises because improving one technical system parameter impacts negatively on another one. For example, making a product lighter by reducing its thickness also makes the product more prone to being easily damaged [13]. However, using better materials increases the cost of manufacturing the product. When confronted with a technical contradiction, a contradiction matrix can normally be used to analyze the problem. Thus, the contradiction matrix is the key analytical tool of TRIZ, as well as a basic technique for technical deconstruction and innovation.

The aim of TRIZ is to avoid conflicts between different elements. Hence, Altshuller identified 39 engineering parameters that often produce technical contradictions. In the matrix, each cell indicates the principles used to resolve these contradictions. The matrix provides a fast and simple way to find solutions to technical contradictions. The matrix is a 39 × 39 matrix. To resolve the contradictions, Altshuller [14] proposed a set of 40 inventive principles. For each contradiction, several principles are suggested to resolve the contradiction. Selecting relevant inventive principles can help the user to produce a solution to the contradictions.

Loh et al. [15] argue that TRIZ is a method of knowledge extraction that can be applied systematically to resolve issues in the area of innovation and improvement. Nakagawa [16] argues that TRIZ is an advanced methodology, which uses a contradiction matrix and 40 inventive principles to provide clear answers to complex problems.

Figure 1 shows an example of a contradiction matrix. In the example, for the improving feature of the area of a moving object (5), the worsening feature is the volume of the moving object (7). From the contradiction matrix, we can identify four inventive principles (4, 7, 14, and 17) to resolve the contradiction. However, if we choose the improving and worsening parameters of productivity (39), we find that the contradiction matrix shows a blank cell, indicating the absence of inventive principles that can provide a solution to the problem. For information on the contradiction matrix and inventive principles, please see http://www.innovation-triz.com/TRIZ40/.

2.2. Taguchi's Method. Taguchi's method is derived from traditional experimental design methods. This method was developed by Genichi Taguchi in 1949. When applied in designing communication systems, it enables the number of experiments to be reduced and at the same time identifies problems in such systems [17]. The method advocates using the orthogonal array function combined with a simple function evaluation process to achieve improvements in the manufacturing process and product design [18].

Taguchi et al. [19] point out that Taguchi's method uses parameter design to improve quality; that is, for product target functions that need improvement, the factors and levels that affect the target functions are identified. Subsequently, orthogonal arrays are used to determine the configuration of the experimental factors and the number of experiments in order to obtain the same information provided by a full factorial experiment with a smaller number of experiments,

analyzing a small amount of experimental data to increase product quality effectively.

Zhang et al. [20] and Yildiz [21] point out that the main tools in Taguchi's method are orthogonal arrays and S/N ratios, emphasizing the importance of quality issues in the product or during the design and manufacturing process. A tolerance design is used to reduce product performance variation. ANOVA is then used to find the level of influence of each significant factor. The tolerance of each significant factor is set based on the costs of each factor, ensuring that product quality variation is minimal and achieving the most appropriate level of quality, thereby realizing robust design objectives.

Yildiz [22] points out that Taguchi's method applies engineering knowledge to experiment planning, focusing on solutions to achieve objectives. As the experimental results obtained by Taguchi's experimental design methods have a high degree of reproducibility, the configuration of experimental factors is straightforward, the number of experiments required is reduced, and the method of analysis is simple and easy to understand. Because of these advantages, Taguchi's method has been applied in many industries to improve and optimize design parameters. For instance, Su et al. [23] use Taguchi's dynamic approach to increase optical whiteness effectively. Hong [24] uses Taguchi's method to identify important factors in market segmentation. In addition, Celani de Souza et al. [25] have shown that Taguchi's method can improve the quality of dialysis. Yildiz [26] uses an immune algorithm and Taguchi's method to design a new design optimization framework.

Taguchi's method specifies the objective function as a certain signal-to-noise ratio (S/N ratio). According to this method, the S/N ratio for different quality characteristics can be separated into larger-the-better (LTB), nominal-the-best (NTB), and smaller-the-better (STB). This study is concerned with improving the uniformity of solder paste thickness in the solder paste printing process. Therefore, NTB is applied out of these quality characteristics. The calculation of the S/N ratio is shown in the following formula (1):

$$S/N_{\mathrm{NTB}} = 10 \cdot \log_{10}\left(\frac{y^2}{s^2}\right), \tag{1}$$

where y is the sample mean and s is the sample standard deviation. The variability characteristic is inversely proportional to the S/N ratio. This means that a larger S/N ratio corresponds to a more robust system.

3. Research Methods

TRIZ and Taguchi's method are alternative experimental design methods used by enterprises to develop new products and improve product quality. The two approaches are often used separately. The TRIZ contradiction matrix enables technical variables that influence quality characteristics to be quickly identified. Although such an approach is able to identify inventive principles, it can only help users to speculate about solutions. The two methods show a wide variation in their experimental efficiency and additivity. Taguchi's method can identify a more optimal value from preset factor levels. However, these variables do not necessarily have a significant effect on quality characteristics.

Therefore, this study attempts to combine TRIZ and Taguchi's method, screening variables that have a significant influence on quality characteristics by linking factors that cause uneven solder paste in the solder paste printing process to the 39 engineering parameters in the TRIZ contradiction matrix, before applying Taguchi's method to the screened variables to identify the optimum process parameter set. The steps are as follows.

(1) Determine experimental variables: list the factors affecting the evenness of solder paste during the solder paste printing process, integrate the 39 engineering parameters in the TRIZ contradiction matrix to create a correlation table and produce a ranking, screening the variables that have a significant effect on quality characteristics.

(2) Design and run experiment: use the orthogonal array function from Taguchi's method for experiment design, the number of repetitions, and conduct the experiment; calculate the S/N ratio and mean. Process managers, engineers, and quality assurance personnel select the levels based on the analysis and discussion of variables that have a significant influence and their range.

(3) Optimization analysis: a two-phase optimization analysis is carried out on experimental data to identify the optimum combination and predict the optimum model for the manufacturing process.

(4) Maximize the S/N ratio: this study uses the delta value and percent combination suggested by scholars to select important influence factors. We identified experiment factors with a delta value greater than the average effect value and a pooled error smaller than 15% as important influence factors and the point closest to the target level as the optimum level of influence factors.

(5) Move the mean closer to the target value: at this stage, the selection has no effect on the S/N ratio. However, factors that have a significant effect on the mean are adjustable, moving the mean closer to the target value.

(6) Forecast optimization: applying the additive model, the expected S/N ratio and estimated mean for the optimal combination condition are calculated based on the set levels of the significant influence factors.

(7) Confirmation tests: confirmation experiments are run on the optimum combination produced using Taguchi's method. This result is then compared with the predicted results using Taguchi's method to confirm the improvement in results.

4. Case Study

4.1. Determine Experiment Variables. This study uses the SMT solder paste printing process for PCB production by

Table 1: Correlation table between factors influencing the uneven thickness of solder paste and 39 technical parameters.

Technical parameters	Influence factors												
	1 Work temperature	2 Work humidity	3 Solder paste type	4 Solder paste proportion	5 Squeegee angle	6 Squeegee pressure	7 Squeegee speed	8 Ejection speed	9 Solder paste poise	10 Stencil tensity	11 Squeegee stencil thickness	12 PCB flatness	13 Working platform flatness
1													
2						V							
3					V	V		V	V				
4							V	V		V		V	
5					V			V	V	V			V
6						V	V	V	V	V	V	V	
7													
8													
9					V		V	V	V				V
10						V						V	
11				V	V	V	V		V	V	V	V	
12					V	V	V	V	V	V	V	V	V
13	V	V	V	V	V	V	V	V	V		V	V	
14			V	V	V	V	V	V		V	V	V	
15													
16					V								
17	V												
18													
19													
20													
21													
22													
23													
24													
25						V	V	V	V				
26			V	V	V	V	V	V	V				
27	V	V	V	V	V	V	V	V	V	V	V	V	V
28	V				V	V	V	V		V	V	V	
29													
30			V										
31			V										
32													
33													
34													
35													
36													

Table 1: Continued.

Technical parameters	Influence factors												
	1 Work temperature	2 Work humidity	3 Solder paste type	4 Solder paste proportion	5 Squeegee angle	6 Squeegee pressure	7 Squeegee speed	8 Ejection speed	9 Solder paste poise	10 Stencil tensity	11 Squeegee stencil thickness	12 PCB flatness	13 Working platform flatness
37				∨		∨		∨					∨
38					∨					∨			∨
39				∨									∨
Number of correlations	4	2	6	7	12	13	11	12	10	9	7	9	7
Ranking	12	13	11	8	2	1	4	2	5	6	8	6	8

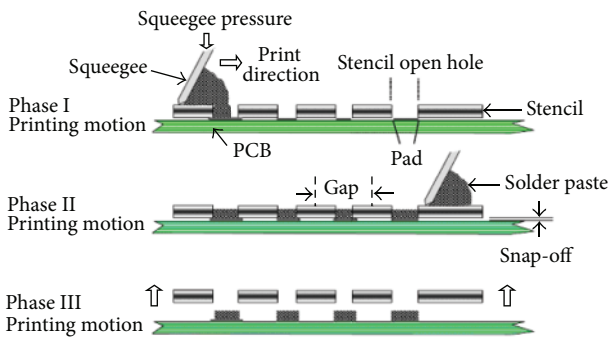

Figure 2: The solder paste printing process.

a multinational company as a case study to investigate the uniformity of solder paste application. The main purpose of solder paste in PCB is to fix parts to the PCB to ensure that the product functions normally. Solder paste printing is the first stage of the SMT manufacturing process. A stencil and solder paste printer squeeze are used to insert the solder paste onto corresponding pads in the PCB through holes in the board. After removing the stencil, the solder paste is left on the pad in the correct shape, completing the printing process, as shown in Figure 2.

Table 1 shows 13 factors that directly influence the thickness of solder paste during the SMT solder paste printing process used in the production of printed circuit boards as selected by process managers, engineers, and quality assurance personnel in the plant. These are then combined with 39 technical parameters in the TRIZ contradiction matrix to produce a correlation table showing the relationship between the 13 factors and 39 technical parameters. Finally, we screen the squeegee angle, squeegee pressure, squeegee speed, and ejection speed as the four variables that have a significant influence on quality characteristics.

4.2. Design and Run the Experiment. We carry out the experiment on the squeegee angle, squeegee pressure, squeegee speed, and ejection speed as the four variables that have a significant influence on quality characteristics. The experimental design uses the $L_9(3^4)$ orthogonal array function proposed by Taguchi's method. The process managers, engineers, and quality assurance personnel select the levels based on the analysis and discussion of their range. Because this study is aimed at improving the uniformity of solder paste thickness during the solder paste printing process, the quality characteristic applied is that of nominal-the-best (NTB). The calculation of the S/N ratio is shown in formula (1).

Based on the influence factor and level settings, nine sets of parameter values are input into the solder paste printer to carry out actual PCB printing. The experiment was repeated four times for each run order and the actual solder paste thickness data was recorded. The target value for solder paste thickness is set at 0.15 mm, with an upper limit of 0.20 mm and a lower limit of 0.10 mm. Table 2 shows the $L_9(3^4)$ orthogonal array and results for uniformity.

4.3. Optimization Analysis. Carry out optimization analysis on the experimental data and predict the optimal model for the experimental process.

4.3.1. Maximize the S/N Ratio. Analysis of the influence of each experiment factor (A, B, C, and D) on the uniformity was performed with an S/N response table, using a Minitab 16 software package.

Table 3 shows the orthogonal array and associated experimental results for uniformity with calculated S/N ratios. The S/N response table for uniformity is presented in Table 3. It shows the calculated S/N ratios for each level of experimental factors. The experimental factor that has the strongest influence is determined according to the value of delta as shown in Table 3. The value of delta equals the difference between maximum and minimum S/N ratios for a particular experimental factor. The higher the value of delta, the more influential the experimental factor. The experiment factors and their interactions are sorted in relation to the values of delta.

Following Lee [27], Sheu [28], and Yang's [29] recommendations, this study defines important influence factors as experimental factors that have a value of delta greater than the average effect size. It can be seen from Table 3 that the strongest influence was exerted by squeegee pressure (factor A), squeegee angle (factor B), and ejection speed (factor D).

The ANOVA procedure was used to investigate which design parameters significantly affect quality characteristics. The procedure is performed by separating the total variability of the S/N ratios into contributions by each of the design parameters and the errors. The total variability of the S/N ratio is measured by the sum of the squared deviations from the total mean S/N ratio.

Yildiz [30], Hong [24], Hsiang and Lin [31], and Su and Yeh [32] use percent contribution to carry out decision making. Percent contribution is the pure sum to squares (purse SS) for each factor as a ratio of the total sum to squares (total SS). When the pooled error percentage (ρ_{err}) $\leqq 15\%$, it can be assumed that no important factors have been omitted from the experiment; in other words, pooled error factors are not significant and can be neglected.

An examination of the calculated percent contribution for all experiment factors also shows a very high influence of factor A, factor B, and factor C on the S/N ratios (Table 4).

First, we find that the percent contributions of squeegee pressure (factor A), squeegee angle (factor B), and ejection speed (factor D) are 34.14%, 31.17%, and 19.81%, respectively. Second, the pooled error is less than 15% (14.88%). Therefore, we can assume that no important factors were missed. By analyzing the experiment factors and ANOVA, this study shows that squeegee pressure (factor A), squeegee angle (factor B), and ejection speed (factor D) have significant effects on the contraction rate.

Based on the above analysis, we are able to determine that squeegee pressure (factor A), squeegee angle (factor B), and ejection speed (factor D) are important influence factors in the present study.

Table 2: Experimental design using the $L_9(3^4)$ orthogonal array and results.

Run order	A Squeegee pressure	B Squeegee angle	C Squeegee speed	D Ejection speed	S/N ratio	Mean
1	1	1	1	1	21.2140	0.1725
2	1	2	2	2	21.5987	0.1700
3	1	3	3	3	25.8433	0.1600
4	2	1	2	3	23.3596	0.0850
5	2	2	3	1	19.8540	0.1475
6	2	3	1	2	25.8433	0.1600
7	3	1	3	2	18.1639	0.0775
8	3	2	1	3	20.8458	0.0900
9	3	3	2	1	20.1436	0.1525

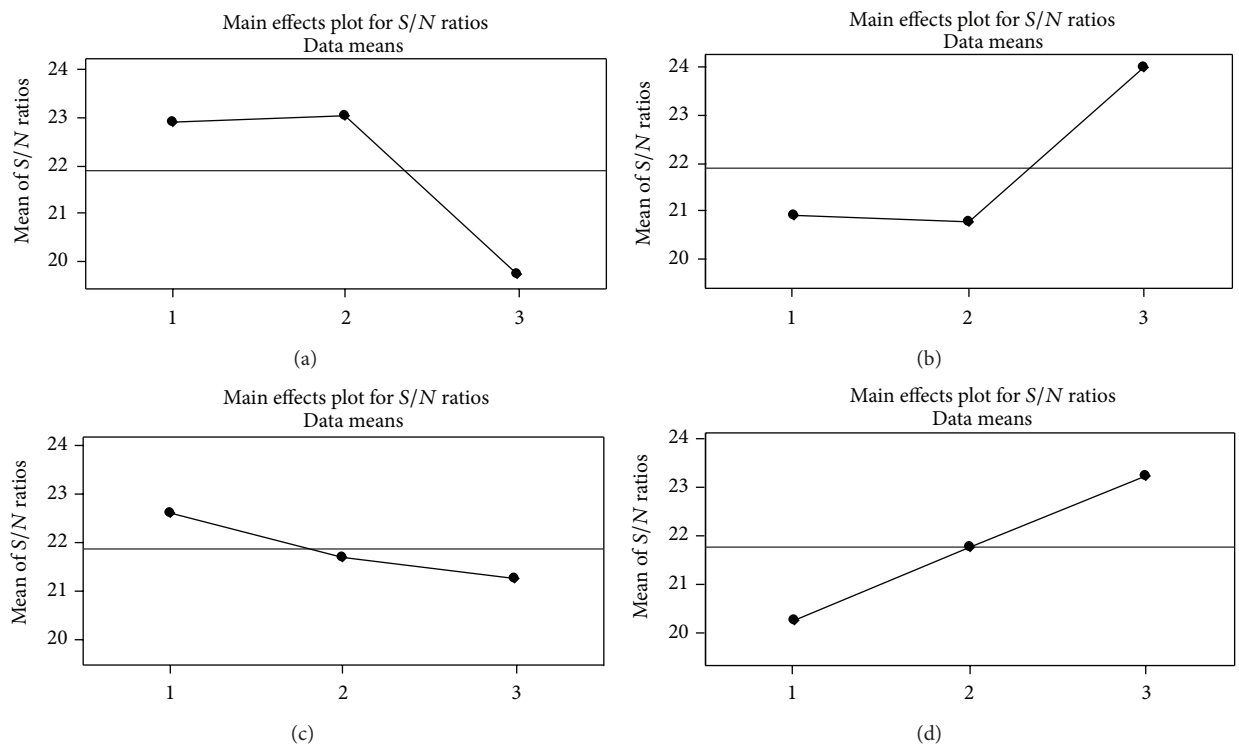

Figure 3: Main effect plots for S/N ratios. Signal-to-noise: nominal-the-best ($10 \cdot \log_{10}(y^2/s^2)$).

Table 3: S/N response table for uniformity.

Level	A	B	C	D
1	22.89	20.91	22.63	20.40
2	23.02	20.77	21.70	21.87
3	19.72	23.94	21.29	23.35
Delta	3.30	3.18	1.35	2.95
Average		2.695		
Rank	1	2	4	3

The plots for S/N ratios are shown in Figure 3. The optimal levels for each experiment factor can be easily determined from these graphs in accordance with Taguchi's "nominal-the-best" performance characteristic. Response graphs show a variation in the S/N ratios when the setting of the experimental factors is changed from one level to another. Figure 3 suggests that the optimum condition for the uniformity is the combination of A_2, B_3, and D_3 levels of the respective experiment factors.

4.3.2. Moving the Mean Closer to the Target Value. At this stage, we select appropriate adjustment factors (with no effect on the S/N ratio, but a significant effect on the mean) to move the mean closer to the target value. Table 5 shows the calculated mean for each level of experiment factors. Table 5 shows that squeegee pressure (factor A), squeegee angle (factor B), and ejection speed (factor D) should be selected as factors that have a significant influence on the mean. However, the above three factors also have a significant

Table 4: Results of the analysis of variance for S/N ratios.

Source	DF	SS	MS	F	Pure SS	Contribution (%)
A	2	20.949	10.475	7.33	18.891	34.14%
B	2	19.303	9.651	6.75	17.245	31.17%
D	2	13.016	6.508	4.55	10.958	19.81%
C + error	2	2.058	1.429		—	—
Pooled error	(2)	(2.058)	(1.429)		8.232	14.88%
Total	8	55.326			55.326	100%

Table 5: Means response table for uniformity.

Level	A	B	C	D
1	0.1675	0.1117	0.1408	0.1575
2	0.1478	0.1358	0.1358	0.1358
3	0.1067	0.1575	0.1283	0.1117
Delta	0.0608	0.0458	0.0125	0.0458

influence on the S/N ratio. Therefore, we do not select any adjustment factors in this step.

Examination of the calculated percent contribution for all experiment factors also shows a very high influence of factor A, factor B, and factor D on the means: see Table 6.

First, we find that the percent contributions of squeegee pressure (factor A), squeegee angle (factor B), and ejection speed (factor D) are 44.29%, 23.96%, and 23.96%, respectively. From the aforementioned analysis, we are able to determine that squeegee pressure (factor A), squeegee angle (factor B), and ejection speed (factor D) have significant effects on the contraction rate for means.

Based on the previous discussion, this study sets the optimal factor level to $A_2\ B_3\ C_1\ D_3$.

4.3.3. Forecast Optimization. Based on the previous discussion, this study sets the optimal factor level to $A_2\ B_3\ C_1\ D_3$. Therefore, the additive model is used to estimate the expected S/N ratio and mean under optimal conditions.

The mean S/N ratio for the nine experiments is $\overline{\eta} = 21.874$ db, and the predicted S/N ratio under optimal conditions is

$$\begin{aligned}\hat{\eta} &= \overline{\eta} + (A_2 - \overline{\eta}) + (B_3 - \overline{\eta}) + (D_3 - \overline{\eta}) \\ &= 23.02 + 23.94 + 23.35 - (2 * 21.874) \\ &= 26.562 \text{ db.}\end{aligned} \tag{2}$$

Similarly, the mean observation for the nine experiments is $\ddot{y} = 0.1350$ mm, and the predicted mean under optimal conditions is

$$\begin{aligned}\hat{y} &= \ddot{y} + (A_2 - \ddot{y}) + (B_3 - \ddot{y}) + (D_3 - \ddot{y}) \\ &= 0.1478 + 0.1575 + 0.1117 - (2 * 0.1350) \\ &= 0.147 \text{ mm.}\end{aligned} \tag{3}$$

4.4. Confirmation Tests. The confirmation experiment under optimal conditions produced 25 individual values and 5 S/N ratios. To confirm that optimal conditions can be reproduced, it is necessary to estimate the confidence interval of the S/N and mean. Su [33] recommends using the formula proposed by Ross [34] to calculate the confidence interval in order to facilitate confirmation experiments. Some scholars [35, 36] suggest that the S/N ratio should be within ±3 db of the optimal value as the basis for assessing the confidence interval in reproduced experiments. Therefore, combining the aforementioned recommendations, this study uses Ross' proposed formula to calculate the confidence interval. However, when the calculated confidence interval exceeds ±3 db, the level is set at ±3 db:

$$\text{CI} = \sqrt{F_{\alpha,1,v2} \times V_e \times \left[\frac{1}{n_{\text{eff}}} + \frac{1}{r}\right]}, \tag{4}$$

where CI is the confidence interval, $F_{\alpha,1,v2}$ is value F at the significance level, α, α is the significance level, V_2 is the degree of freedom of the pooled error, V_e is the variance of the pooled error, n_{eff} is the effective number of observations, and r is the number of repeated confirmation experiments.

The S/N ratio and mean confidence intervals for confirmation experiments under optimal conditions are

$$\begin{aligned}\text{CI}_{S/N} &= \sqrt{F_{\alpha,1,v2} \times V_e \times \left[\frac{1}{n_{\text{eff}}} + \frac{1}{r}\right]} \\ &= \sqrt{18.51 \times 1.429 \times \left[\frac{7}{9} + \frac{1}{5}\right]} \\ &= 5.09 \text{ db,}\end{aligned} \tag{5}$$

as $\text{CI}_{S/N} = 5.09$ db > 3 db; therefore the S/N ratio confidence interval is ±3 db,

$$\begin{aligned}\text{CI}_{\text{mean}} &= \sqrt{F_{\alpha,1,v2} \times V_e \times \left[\frac{1}{n_{\text{eff}}} + \frac{1}{r}\right]} \\ &= \sqrt{18.51 \times 0.000119 \times \left[\frac{7}{36} + \frac{1}{25}\right]} \\ &= 0.023 \text{ mm.}\end{aligned} \tag{6}$$

The average of the five confirmation experiments is as follows: S/N ratio = 26.632 db and mean = 0.155 mm. These two values fall entirely within the corresponding confidence intervals, indicating that the experiment achieved an improvement. The comparison of values before improvement

Table 6: Results of the analysis of variance for means.

Source	DF	SS	MS	F	Pure SS	Contribution (%)
A	2	0.005629	0.002815	23.70	0.005392	44.29%
B	2	0.003154	0.001577	13.28	0.002917	23.96%
D	2	0.003154	0.001577	13.28	0.002917	23.96%
C + error	2	0.000237	0.000119		—	—
Pooled error	(2)	(0.000237)	(0.000119)		0.000949	7.79%
Total	8	0.012175			0.012175	100%

Table 7: Comparison of values before improvement (current), forecast optimization, and confirmation experiments.

	Before improvement (current)	Forecast optimization	Confirmation experiment
S/N ratio	21.732db	26.562 db	26.632 db
Mean	0.163 mm	0.147 mm	0.155 mm

(current), forecast optimization, and confirmation experiments is shown in Table 7.

Confirmation experiments are run on the optimum combination produced using Taguchi's method. This result is then compared with the predicted results using Taguchi's method to confirm the improvement in results.

5. Conclusion

In this study, the S/N ratio improved from 21.732 db to 26.632 db, while the mean also improved from the current 0.163 mm to 0.155 mm, indicating a reduced variation. In addition, the mean was closer to the target value (0.15 mm), showing that applying TRIZ and Taguchi's method for improving the uniformity of solder paste thickness in the solder paste printing process is feasible.

This study revised the TRIZ contradiction matrix to investigate the correlation between contradiction matrix parameters and parameters that directly influence the uneven thickness of solder paste in the solder paste printing process, screening the squeegee pressure, ejection speed, squeegee speed, and squeegee angle as the key parameters affecting the quality of SMT solder paste thickness. This is an innovative approach that is empirically shown to be feasible.

Taguchi's method is used to establish an optimal parameter set from the experimental data, with the prediction error rate reaching the required accuracy and delivering real improvements in process capability and product quality. These improvements can help lower the defect rate and reduce production costs, while shortening delivery times and increasing customer satisfaction. These results may help Taiwan's SMT assembly factories to increase product quality, explore further different machines and productivity factors, and compare different level parameters to produce even better process parameters for realizing additional quality improvements.

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