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MONITORING OF THE STENCIL PRINTING PROCESS USING A MODIFIED REGRESSION RESIDUAL CONTROL CHART: AN EMPIRICAL STUDY

[1]Tsung-Nan Tsai and [2]Long-Hui Chen

[1]Department of Logistics Management, Shu-Te University, Kaohsiung, 82445, Taiwan
[2]Department of Business Management, National Kaohsiung Normal University, Kaohsiung, Taiwan
Corresponding author's e-mail: {Tsung-Nan Tsai, tntsai@mail.stu.edu.tw}

This paper focuses on developing a regression residual control chart to economically detect the abnormal patterns of the stencil printing process (SPP), in order to predict significant deviations that might result in nonconforming products. The SPP is widely recognized as the main contributor of soldering defects in a surface mount assembly (SMA). The earlier those abnormal conditions can be detected in the SPP stage, the less expensive the defect correction costs. Shewhart control chart is frequently used to monitor the amount of solder paste volume. Its results, however, can be error-prone since the solder paste volume is significantly affected by other process factors. For developing the proposed control chart, a 3^{8-3} experimental design was first conducted and validated to formulate the relationship between the control variables and the SPP response. Eight process factors for SPP were initially defined, including stencil thickness, component pitch, aperture area, snap-off height, squeegee speed, squeegee pressure, solder paste viscosity, and solder paste type. The control variables of the SPP can be expressed as a linear regression function, and a regression residual control chart can then be constructed using the significant variables through the results of ANOVA analysis. Finally, the proposed control chart is employed to detect out-of-control conditions of the SPP. A Monte-Carlo simulation and an empirical evaluation were also carried out to demonstrate the effectiveness of the proposed methodology. The empirical evaluation shows that the proposed regression residual control chart provides approximately 90% of detection accuracy for the SPP.

Significance: The proposed modified regression residual control chart can economically detect the abnormal patterns of the stencil printing process (SPP) and the empirical evaluation demonstrates the proposed methodology can provide high detection accuracy of the control chart pattern for the SPP to prevent printing defects and high rework costs for mass production.

Keywords: Surface mount assembly, regression control chart, stencil printing, experimental design, statistical process control.

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1. INTRODUCTION

1.1 Surface mount assembly

Surface mount technology (SMT) is the most commonly used means for assembling the printed circuit boards (PCBs) used in sophisticated electronic devices (Amir, 1994). During the first step of the assembly process, stencil printing, a squeegee is used to force solder paste into the stencil apertures covering the pad on the PCB, as illustrated Figures 1 (a) and (b). It is important that the amount of solder paste necessary to produce consistent printing patterns be deposited to increase the first-pass yield. The surface mount devices (SMDs) are then mounted on the pasted pads by a chip shooter, and finally, the fabricated boards undergo reflowing in a reflow furnace, where solder joints are formed without altering the initial mechanical and electronic characteristics of the components, as shown in Figure 1(c). The need for an ever higher pin count, better performance, smaller size and lighter weight has driven the development of fine pitch and ultra-fine stencil printing applications to produce such advanced package types as the Shrink Quad Flat Package (SQFP), Thin Small Outlined Package (TSOP), Ball Grid Array (BGA) and Flip Chip.

In practice, an assembled PCB passes through a multiple stage surface mounting process. It is recognized that, in a multistage manufacturing systems, the quality of the output of some stages will be significantly affected by the output quality of the preceding stages (Zantek et al., 2006). Defect correction (repair and rework) costs can vary, but usually the cost increases five to tenfold with each successive production step in the surface mount assembly (SMA) process (Ries, 2000). The stencil printing process (SPP) is widely recognized as the main contributor of soldering defects in an SMA, causing approximately sixty percent of soldering defects (He et al., 1998). The other soldering defects occur in successive manufacturing stages (see Figure 2). Thus, the earlier the abnormal conditions can be detected in the SPP stage, the less expensive the defect correction costs. An even more cost-effective strategy would be to detect abnormal patterns in the volume of solder paste deposited so as to improve the first-pass yield early on in the stencil printing application. Accordingly, one of the main challenges towards an effective and efficient SMA is to properly monitor the SPP.

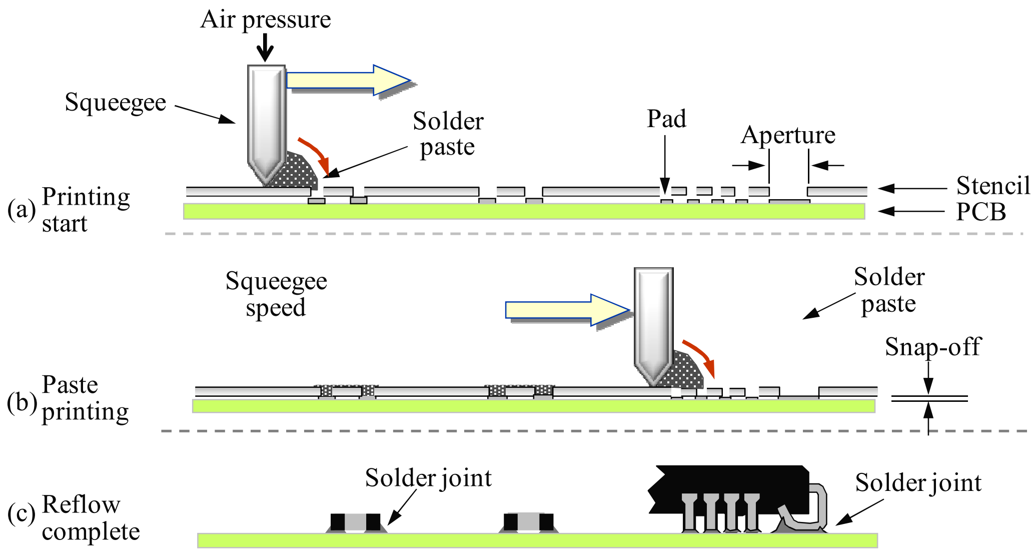

Figure 1. Surface mount assembly process

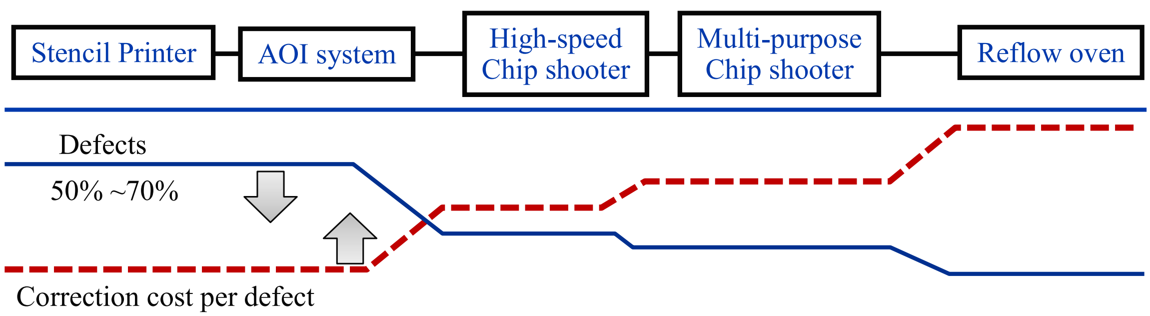

Figure 2. Opportunity/cost for the defect detection and correction in a surface mount assembly (Adapted from Kelley and Tan, 2003)

1.2 Statistical process control

In statistical process control (SPC), statistical tools can be used to effectively monitor the manufacturing process. For example, control charts can be used to predict significant deviations that may later result in product nonconformity (Guh and O'Brien, 1999; Roberts, 2005). A control chart is usually used to monitor both the process mean and variation about that mean. The charts can be used to identify the presence of assignable causes by continuously monitoring the process output. Statistics related to sample data drawn from the process are plotted on a control chart with predefined control limits. Any point plotted outside the control limits indicates an out-of-control condition. Therefore, practitioners can nonconformities early, seek possible causes for the occurrence of the variations, and take necessary corrective action to return the process to normal, all by using a control chart. Consequently, variations in the process that may affect the quality of the end product can be detected and corrected, thus reducing waste.

1.3 Regression control chart

There are many versions of the regression control chart that can be employed to improve manufacturing process control and product yield. An enormous number of useful industrial applications based on regression control charts have been developed, for example, the Shewhart control chart for regression residuals, the exponentially weighted moving average (EWMA) control for regression control charts, and so on. Monitoring the dependent variable is the core idea behind a regression control chart. Mandel (1969) developed a regression control chart for work in conjunction with administrative applications. Zhang (1984) developed a cause-selecting chart (CSC), which is similar to a regression control chart and can be used to distinguish the occurrence of quality problems across manufacturing processes. Wade and Woodall (1993) reviewed several CSCs and found that the quality characteristics must be controlled simultaneously. Shu et. al. (2005) investigated the effect of parameter estimation errors on the performance of CSCs. After parameter estimation, the findings indicate that the charted statistics are correlated. Shu et. al. (2004) discussed the run-length performance of regression control charts based on estimated parameters for the manufacturing process. May and Sulek (2008) proposed an alternative regression control chart based on least absolute value regression for limited process data and provided a series of control charting procedures used to identify the variables that are significant to an out-of-control condition. The regression adjustment approach can be especially beneficial to further control charting (Hawkins, 1991, 1993; Hawkins and Olwell, 1998). For more detailed information about the regression control charting, interested readers are referred to Crocker (1985), Montgomery and Peck (1992) and Ryan (1997).

A regression control chart necessitates the integration of linear regression. According to control chart theory only a least squares regression model is required to process data prior to constructing the control chart (Montgomery, 2001). The development of the regression residual control chart is briefly described below.

Let X denote the control variables, and let Y be the output characteristics of interest. The first step is to fit a linear equation that relates X to Y from the paired observations (X_k, Y_k) gathered from the manufacturing process. The regression residual control chart is constructed based on the values of Y adjusted for the effects of X, namely the regression residuals. A simple multiple regression equation can thus be obtained.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon, \quad k = 1,2,...,n, \qquad \cdots \qquad (1)$$

where k denotes the control variables, and the error term ε, and β_0, β_1, …, β_k are the respondent regression coefficients. The error term ε is independent and normally distributed with a mean of zero (μ=0) and has a constant variance of σ^2.
The regression equation (Eq. (2)) is then derived by minimizing $\sum \varepsilon^2$. It can now be used to predict the responses (Y) for the control variables X

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \cdots + \hat{\beta}_k X_k \qquad \cdots \qquad (2)$$

where $\hat{Y}, \hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \cdots, \hat{\beta}_k$ and $\hat{\sigma}$ are the estimators of $Y, \beta_0, \beta_1, \beta_2, \cdots, \beta_k$ and σ. Once the parameter estimates $\hat{Y}, \hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \cdots, \hat{\beta}_k$ are obtained, the corresponding residual given a future paired observation at time t, $\left(X(t), Y(t)\right)$, is

$$e(t) = Y(t) - \hat{Y}(t) = Y(t) - (\hat{\beta}_0 + \hat{\beta}_1 X_1(t) + \hat{\beta}_2 X_2(t) + \cdots + \hat{\beta}_k X_k(t)) \qquad \cdots \qquad (3)$$

The standardized residual, $e(t)/\hat{\sigma}$, related to sample data drawn from the process are plotted on a control chart with predefined control limits. Hence, the regression control chart can be constructed to monitor the process.

The remainder of this paper is organized as follows: Section 2 we present an empirical illustration of the proposed modified regression residual control chart, followed by a step-by-step discussion. Some concluding remarks are made in section 3.

2. EMPIRICAL ILLUSTRATIONS

The SPP and ultimate soldering quality are sensitive to the solder paste deposition volume because the solder paste deposited volume acts as a major response and control point in the SPP. An important topic is how to effectively apply a tool to monitor the soldering quality of the SPP. A traditional method uses the Shewhart control chart, one of the statistical process control (SPC) tools, to monitor directly the process output of interest, the solder paste deposition volume. However, the results are likely to be error-prone since the solder paste deposition volume is significantly affected by other process factors simultaneously. To solve the problem of the simultaneous affects, a modified regression residual control chart is proposed. The procedure employed to develop the modified regression residual control chart is depicted in Figure 3. First, the control and response variables of the SPP must be defined, followed by a design of experiment (DOE). Then a regression equation is derived and validated to properly fit X to Y. Next, the most important variables are identified using

ANOVA analysis and used to construct the regression residual chart. Finally, a Monte-Carlo simulation and an empirical evaluation are conducted to assess the effectiveness and detection accuracy of this proposed methodology.

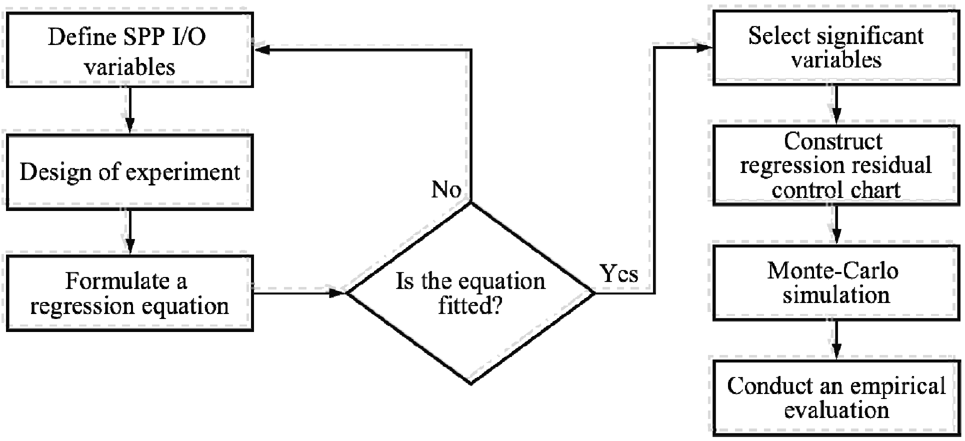

Figure 3. Development flow of the modified regression residual control chart

2.1 Defining the SPP control and response variables

The stencil design, solder paste, operating parameters, stencil printer, substrate and squeegee all have an influence on the SPP performance (Mannan et al., 1994; Lau and Yeung, 1997; Markstein, 1997; He et al., 1998; Lofti and Howarth, 1998). Researchers addressing SPP performance, however, have areas of disagreement. According to the literature review and expert knowledge, there is no universally accepted criterion for selecting the control variables of the paste stencil printing process. Therefore, on the basis of preliminary studies, we selected eight variables for the preliminary DOE, which include *stencil thickness*, *component lead-pitch*, *aperture size*, *snap-off distance*, *squeegee speed*, *squeegee pressure*, *solder paste viscosity*, and *solder paste type*. These variables are used to investigate the nonlinear relationships between control variables and the process response, as shown in figures 1(a) and 1(b). The SPP and ultimate soldering quality are sensitive to the solder paste deposition volume. Thus, the deposition *volume* of solder paste acts as a response and becomes the major control point in the SPP.

2.2 Design of experiment

The DOE method is widely used in research as well as in industrial applications. The primary goal is usually to show the statistical significance of an effect that a set of particular factors will exert on the dependent variable of interest. For the sake of collecting the structured data and minimizing experimental aberration, Franklin's (1984) DOE development scheme, which is a three-level fractional factorial experimental design (3^{k-p}), is employed in this study. Following the given DOE scheme, the matrix C shown below provides the design through the range $1 \le p, k - p \le 6$

$$C = \begin{vmatrix} 2 & 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 2 & 1 & 2 \\ 1 & 0 & 2 & 1 & 1 & 1 \\ 0 & 2 & 1 & 1 & 1 & 2 \\ 1 & 1 & 1 & 1 & 2 & 0 \\ 1 & 2 & 1 & 2 & 0 & 1 \end{vmatrix}.$$

The first p rows and $k–p$ columns are selected and the $p \times p$ unit matrix is appended for generating the orthogonal arrays. For a 3^{8-3} design, the following matrix is derived:

$$C = \begin{vmatrix} 2 & 1 & 1 & 0 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 2 & 1 & 0 & 1 & 0 \\ 1 & 0 & 2 & 1 & 1 & 0 & 0 & 1 \end{vmatrix}.$$

Let X_i be the standard value of control factor i, 0 represents the lowest value, 1 denotes the middle value, and 2 stands for the highest value. As the derived matrix list above, A total of 243 ($=3^{8-3}$) runs were required to satisfy equations (4) to (6).

$$2X_1 + X_2 + X_3 + X_5 + X_6 = 0 \pmod 3 \quad \ldots \quad (4)$$
$$X_1 + X_2 + 2X_4 + X_5 + X_7 = 0 \pmod 3 \quad \ldots \quad (5)$$
$$X_1 + 2X_3 + X_4 + X_5 + X_8 = 0 \pmod 3 \quad \ldots \quad (6)$$

In this experiment, three customized laser-cutting stainless stencils having the same pattern (see Figure 4), but with different thicknesses (1.0 mm, 1.2 mm, and 1.5 mm) and area ratios (85%, 100%, and 115%) (Measured as the percentage of PCB pad size) were built. To facilitate the experiment the laser-cut patterns were articulated with different component lead pitches onto the same stencil. The three levels for each control variable were determined after preliminary analysis and discussion with senior process engineers. The resultant levels for each factor are shown in Table 1.

Table 1. Input factor levels

Control variables	Level I	Level II	Level III	Symbols
1. Stencil thickness (mm)	1.0	1.2	1.5	Sten_thk
2. Lead pitch (mm/mil)	0.4/16	0.5/20	0.65/25	Lead_pitch
3. Stencil aperture area (%)	85%	100%	115%	Sten_R
4. Snap-off height (mm)	0	1.0	2.0	Snap_off
5. Stroke speed (mm/sec)	20	40	60	S_speed
6. Squeegee pressure (bar)	1	3	5	S_press
7. Paste viscosity (kcps)	800	1050	1300	Viscosity
8. Solder paste mesh size (type)	-200+325 (Type II)	-325+400 (Type III)	-400+500 (Type IV)	S_mesh

The four corners of each QFP package were measured by a 3-D automated optics inspection (AOI) system to determine the amount of volume of solder paste deposition for each experimental run. The vertical and horizontal rows in Figure 5 represent perpendicular and parallel paste volumes, respectively. The average of the vertical and horizontal volumes can be calculated by $(\sum_{i=1}^{4} P_i + \sum_{j=1}^{4} V_j)/8$. For TSOP-32 (0.5 mm pitch), for instance, the average volume can be calculated by dividing the sum of the deposited volume at the four corners of the package by four. The average volume is an indicator of potential quality problems such as excessive solder, insufficient solder, bridge, void, *etc*. In practice, the proper volume ranges are predetermined as control limits for quality control.

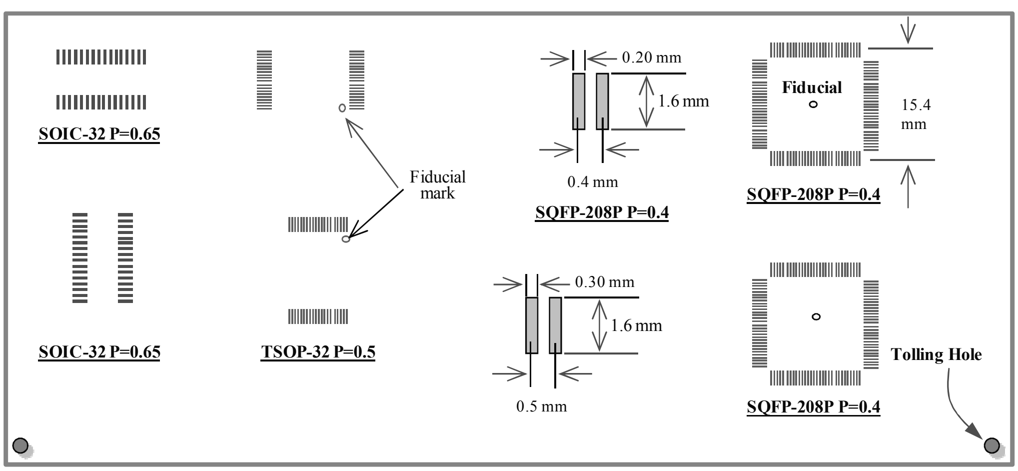

Figure 4. Customized laser-cut stencil design

2.3 Construction of a prediction reference regression equation

In order to construct a prediction regression equation for the reference model, a set of "normal" observations must be collected. Eight SPP control variables are collected, which are used in the formulation of the regression model (by using Eq.

(1)) from the DOE. A set of "normal" observations (131 samples) are gathered from experimental data. Since the control variables, component lead pitch (Lead_pitch) and solder paste type (S_mesh) have categorical attributes, dummy variables are necessary to represent these two control variables. The eight variables are rescaled, as illustrated in Table 2. With the exception of categorical variables, the rest of the variables keep their original values.

The regression equation is obtained by minimizing $\sum\varepsilon^2$. This can now be used to predict the response of variable Y corresponding to the control variables X, as illustrated in Eq. (7)

$$\hat{Y} = -1734.35 + 2237.35 \cdot X_{1\_1} + 5618.97 \cdot X_{1\_2} - 204.93 \cdot X_{2\_1} + 9.18 \cdot X_{2\_2} - 14.43 \cdot X_3 - 2.89 \cdot X_4 + 56.02 \cdot X_5$$
$$+ 31.38 \cdot X_6 + 13503.77 \cdot X_7 + 0.29 \cdot X_8 \quad \ldots \quad (7)$$

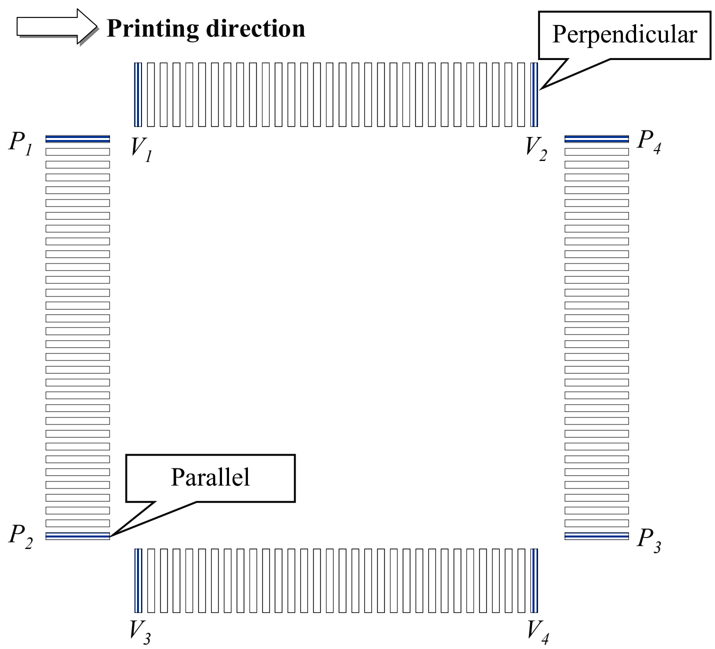

Figure 5. Locations of solder paste volume measures

Table 2. Rescaled variables and values

Control variables	Attributes	Rescaled value	Variable name
Lead pitch	Categorical	0.4 mm→(0, 0) 0.5 mm→(1, 0) 0.65 mm→(0, 1)	X_{1_1}, X_{1_2}
Solder paste type	Categorical	Type II→(0, 0) Type III→(0, 1) Type IV→(1, 0)	X_{2_1}, X_{2_2}
Squeegee pressure	Continuous	1, 3, 5 (Original value)	X_3
Squeegee speed	Continuous	20, 40, 60 (Original value)	X_4
Snap-off height	Continuous	0, 1, 2 (Original value)	X_5
Stencil aperture Ratio	Continuous	85, 100, 115 (Original value)	X_6
Stencil aperture area	Continuous	0.1, 0.12, 0.15 (Original value)	X_7
Solder paste viscosity	Continuous	800, 1100, 1300 (Original value)	X_8

2.4 Validation of the regression model and selection of the important variables

The validation of the regression equation is crucial in improving the model's prediction accuracy. ANOVA analysis is applied to identify the feasibility of the regression equation (reference model) derived above. The analysis results are illustrated in Table 3. The R-square value is 0.936 and indicates that the analysis results properly fit X to Y and explain the process variations well.

Hypothesis testing is very useful for the identification of important SPP variables. Let the possibility of type I error be 0.05. The less important control variables, which have a higher p-level (>0.05), can be removed after the hypothesis testing phase. It is found to be true that the factors, component lead pitch (X_{1_1} and X_{1_2}), stencil aperture (X_6), and stencil thickness (X_7) significantly determine the amount of solder paste deposited ($\hat{Y}$).

Table 3. Summary of ANOVA analysis

	Sums of square	***df***	***Mean***	***F***	***p-level***
Regression	607633751	10	60763375	174.8435	0.00
Residual	41703619	120	347530		
Total	649337370				

We ultimately obtain the fine-tuned regression equation

$$\hat{Y} = -1253 + 2199.23 \cdot X_{1\_1} + 5581.01 \cdot X_{1\_2} + 29.66 \cdot X_6 + 12419.08 \cdot X_7 \cdot \qquad \cdots \qquad (8)$$

Eq. (8) provides descriptive information. The component lead pitch (Lead_pitch), stencil area ratio (Sten_R) and stencil thickness (Sten_thk) are the most significant factors in the SPP. Take the corresponding regression coefficients for the factor of Lead_pitch and let the other factors stay unchanged. When Lead_pitch increases from level I (0.4 mm) to level II (0.5mm), the response value ($\hat{Y}$) will increase to 2199.23 mil^3. In the same manner, when Lead_pitch increases from level I (0.5 mm) to level III (0.65 mm), the response value ($\hat{Y}$) will increase to 3381.78 mil^3 (=5581.01-2199.23). The effects for factors Sten_R and Sten_thk can also be derived in the same manner.

2.5 Construction of the regression residual control chart and simulation

Eq. (7) is applied to obtain the predicted values $\hat{Y}$ of the response variable Y for the values of control variables X. The error term ε is independent and normally distributed with a mean of zero (μ=0) and has a constant variance of σ^2. We construct a regression residual control chart to monitor the standardized residual $\left(Y-\hat{Y}\right)/\hat{\sigma}$, where the centerline is 0 and the control limits are ±3. The regression residual control chart is shown in Figure 6. The sample statistics plotted fall within the control limits, signaling that no out-of-control conditions occurred. In many practical cases, however, the patterns of a control chart often exhibit nonrandom behavior which provides useful diagnostic information. Hence, in this study, some of the common patterns that may appear on the regression residual control chart are discussed. A Monte-Carlo simulation approach is used to generate unnatural patterns using the following pattern generation equation:

$$Y(t) = -1253 + 2199.23 \cdot X_{1\_1}(t) + 5581.01 \cdot X_{1\_2}(t) + 29.66 \cdot X_6(t) + 12419.08 \cdot X_7(t) + n(t) + d(t) \qquad \cdots \qquad (9)$$

where t is the time of sampling, $X_{1\_1}(t), X_{1\_2}(t), X_6(t), X_7(t)$ are the given values of the control variables, Lead_pitch, Sten_R and Sten_thk, respectively, at time t, and $n(t)$ is the common cause variation at time t. It follows a normal distribution with a mean of 0 and standard deviation $\hat{\sigma}$. Finally, $d(t)$ is the special disturbance at time t ($d(t)$=0, when no unnatural pattern is present).

Table 4 shows the details of the shifts/trends of unnatural patterns. The corresponding control charts are illustrated in figures 7(a) to 7(d). Some tests that can be conducted to find unnatural patterns are listed below. Interested readers are referred to Nelson (1984) for a more detailed discussion.

Test 1: 1 point more than three standard deviations from center line
Test 2: 9 points in a row on same side of center line
Test 3: 6 points in a row, all increasing or all decreasing
Test 4: 14 points in a row, alternating up and down
Test 5: 2 out of 3 points > two standard deviations from center line (same side)
Test 6: 4 out of 5 points > one standard deviation from center line (same side)
Test 7: 15 points in a row within 1 standard deviation of center line (either side)

Table 4. Details of shifts/trends in unnatural patterns

Pattern type	*d*(*t*)	Description	Quantity
Upward shift	$2\hat{\sigma}$	Offset from the prediction regression reference equation	30
Downward shift	$-2\hat{\sigma}$	Offset from the prediction regression reference equation	30
Upward trend	$0.2t\hat{\sigma}$	Trend	30
Downward trend	$-0.2t\hat{\sigma}$	Trend	30

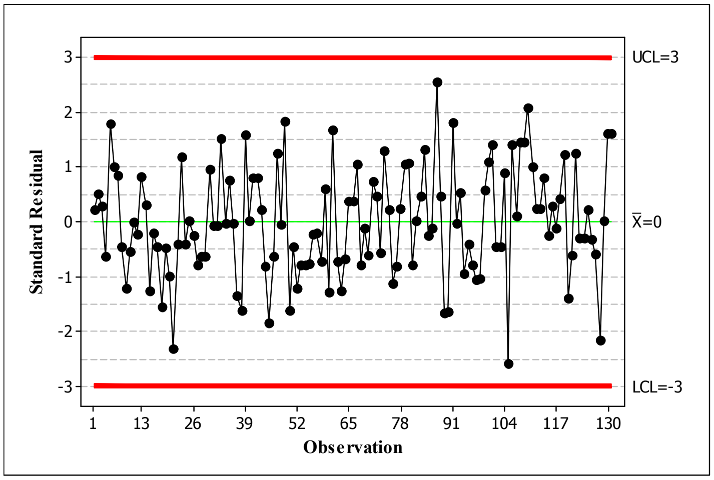

Figure 6. Regression residual control chart

2.6 Empirical evaluation of the regression residual control chart

An additional set of thirty random samples (the most fabricated products with lead pitches 0.5mm and 0.65 mm) was gathered from the historical SPC data library (see Table 5) and used to assess the performance of the proposed regression control chart. The data set contains both normal and unnatural patterns. A resultant regression control chart with data points is generated in Figure 8. Comparing this with empirical SPC data, the residual control chart can easily identify the out-of-control data points. According to the extensive knowledge of domain experts, the evaluation by the proposed regression control chart is satisfactory and provides promise as an effective way to monitor the SPP. Additionally, the proposed control chart can easily be made to engage with automated Macro functions through the designated Microsoft Excel®.

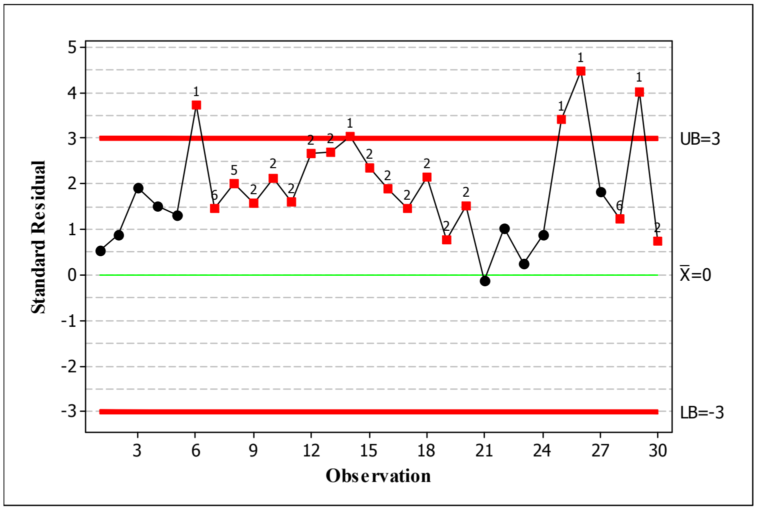

Figure 7(a). The modified regression residual control charts for the abnormal patterns: Upward shift pattern

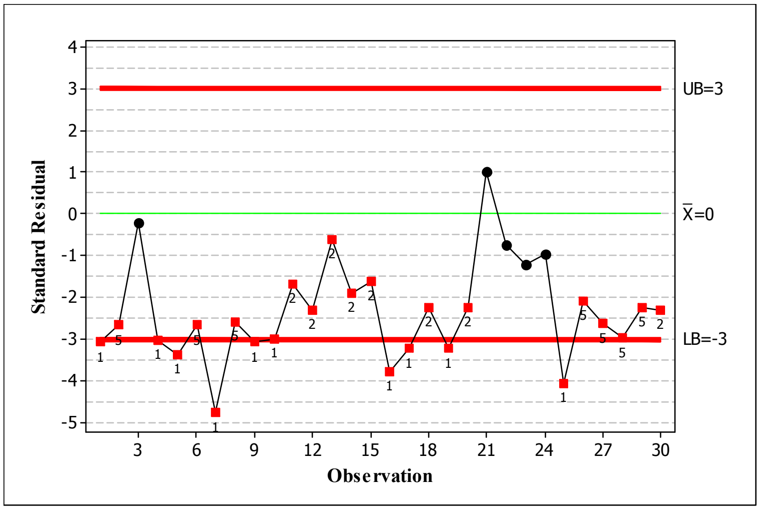

Figure 7(b). The modified regression residual control charts for the abnormal patterns: Downward shift pattern

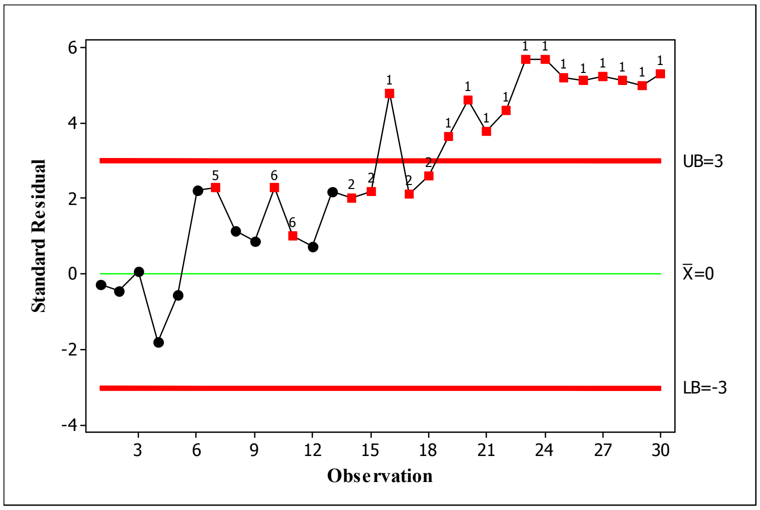

Figure 7(c). The modified regression residual control charts for the abnormal patterns: Upward trend pattern

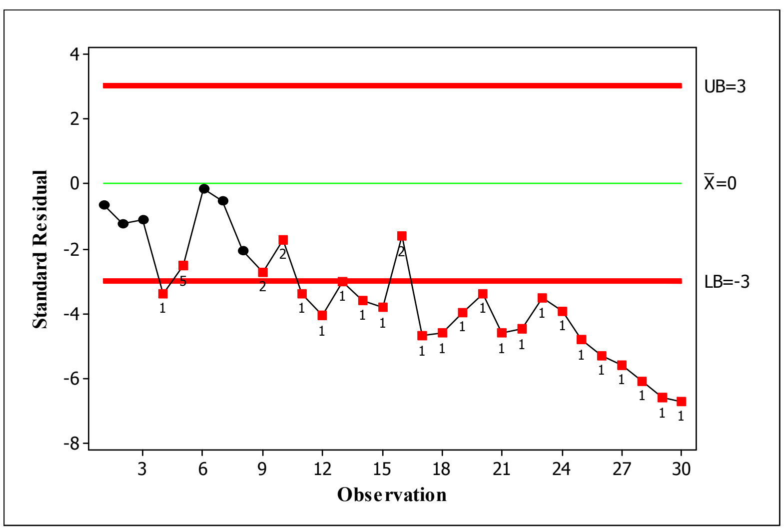

Figure 7(d). The modified regression residual control charts for the abnormal patterns: Downward trend pattern

Table 5. Test data and regression outputs

	L_pitch	L_pitch_X_{1_1}	L_pitch_X_{1_2}	Sten_R	Sten_thk	Actual Volume	Predicted Volume	STD_error
#1	0.5	1	0	100	0.15	4929	5775.092	-1.431126435
#2	0.5	1	0	93	0.15	3875	5567.472	-2.862699519
#3	0.65	0	1	85	0.15	7672	8711.972	-1.758230918
#4	0.5	1	0	85	0.15	4789	5330.192	-0.914567211
#5	0.65	0	1	85	0.15	7145	8711.972	-2.649603299
#6	0.5	1	0	100	0.15	4929	5775.092	-1.431126435
#7	0.65	0	1	85	0.15	7688	8711.972	-1.732014083
#8	0.65	0	1	85	0.15	7688	8711.972	-1.732014083
#9	0.65	0	1	85	0.15	7362	8711.972	-2.282567613
#10	0.65	0	1	85	0.15	6766	8711.972	-3.29191575
#11	0.65	0	1	85	0.15	8463	8711.972	-0.421172347
#12	0.65	0	1	85	0.15	9238	8711.972	0.889669389
#13	0.65	0	1	85	0.15	7634	8711.972	-1.823773005
#14	0.65	0	1	85	0.15	7789	8711.972	-1.561604658
#15	0.65	0	1	85	0.15	8409	8711.972	-0.512931269
#16	0.65	0	1	85	0.15	7688	8711.972	-1.732014083
#17	0.65	0	1	85	0.15	7634	8711.972	-1.823773005
#18	0.65	0	1	85	0.15	8409	8711.972	-0.512931269
#19	0.65	0	1	85	0.15	7207	8711.972	-2.54473596
#20	0.65	0	1	85	0.15	7300	8711.972	-2.387434951
#21	0.5	1	0	85	0.15	4293	5330.192	-1.753505922
#22	0.5	1	0	85	0.15	4293	5330.192	-1.753505922
#23	0.5	1	0	85	0.15	4975	5330.192	-0.599965194
#24	0.5	1	0	100	0.15	4115	5775.092	-2.807510258
#25	0.65	0	1	85	0.15	8215	8711.972	-0.840641703
#26	0.5	1	0	85	0.15	4100	5330.192	-2.081216356
#27	0.65	0	1	85	0.15	5433	8711.972	-5.546563536
#28	0.5	1	0	85	0.15	3929	5330.192	-2.369601538
#29	0.5	1	0	85	0.15	3410	5330.192	-3.247865501
#30	0.65	0	1	85	0.15	7262	8711.972	-2.452977038

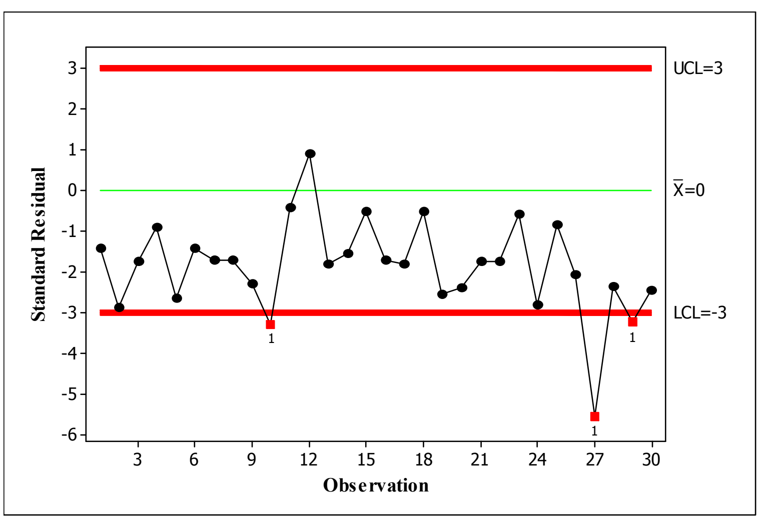

Figure 8. Test regression residual control chart

3. CONCLUDING REMARKS

SMT has become the main manufacturing process in the PCB assembly industry. In practice, an assembled PCB moves through a multiple stage surface mounting process. The output quality of some stages in this multistage manufacturing system is significantly affected by the output quality of preceding stages. SPP is widely recognized as the main contributor of soldering defects in SMA, as it causes an average of sixty percent of all soldering defects. Thus, the earlier the detection of abnormal conditions in the SPP stage, the less expensive the cost of defect correction. A more cost-effective strategy to improve first-pass yield would be to detect any abnormal patterns in solder paste deposited volume early on in stencil printing application.

Traditionally, the SPP has been monitored by a Shewhart control chart that statistics related to the volume of solder paste. Yet, its results can be error-prone since significant control variables affect the process output simultaneously. A 3^{8-3} experiment is designed to investigate the nonlinear relationship between process inputs and response, and to find the significant control factors for the SPP. The experimental data set is utilized to develop a regression residual control chart for detecting the abnormal conditions of the residual deposition volume. A Monte-Carlo simulation and an additional empirical evaluation confirm the effectiveness of the proposed control chart for SPP monitoring. The empirical evaluation shows that the proposed methodology can be used to operatively monitor the SPP.

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BIOGRAPHICAL SKETCH

Tsung-Nan Tsai is an associate professor in Department of Logistics Management at Shu-Te University, Taiwan. He received M.S. degree in School of Management Science from I-Shou University, and PhD degree in Manufacturing Engineering from Chung-Kung University, respectively. He had a 14-year working experience in the electronic industry. His research interests include applications of soft computing, intelligent manufacturing system, quality engineering, and data mining.

Long-Hui Chen is an Associate Professor in the Department of Business Management of National Kaohsiung Normal University, Kaohsiung City, Taiwan. He received his PhD in the Department of Industrial Management Science of National Chang Kung University, Tainan City, Taiwan. His current research interests include statistical process control, data mining and service science management. He has published in journals such as *Expert systems with applications, Computational statistics and data analysis, Journal of intelligent manufacturing, Computers & industrial engineering, Production planning and control and International journal of computer integrated manufacturing.*