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by

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ABSTRACT

A case study of improving the quality of a complex wave soldering process which produces printed circuit boards (PCB) is presented in this article. Experimental design with a mixed-level fractional factorial structure was implemented in a high-volume production system during regular hours of operation. The observed ordered-categorical data from the bottom-side joints of PCB's are weighted to formulate performance measurements such as the average and the uniformity of solder-qualities. These summary statistics take into account the spatial correlation that occurs in joint-quality within the same type of components such as integrated circuit and PGA's. Several polynomial regression models with possible higher-order interactions between controllable variables are fitted to these statistics. Dispersions effects are computed and modeled from repetitions of the average and the uniformity measurements. Topside soldering quality, pre-soldering board temperature and dispersion effects are used to set the constraints for optimizing the average and the uniformity soldering-quality simultaneously. A nonlinear programming method of constrained optimization is employed to determine the best and most robust settings for the continuous and discrete process variables. The analysis of results from a small confirmatory experiment shows a completely uniform soldering-quality and an improvement of 32.85% in mean scores in comparing samples of 20 PCB's taken before and after optimization.

Key Words: Quality Improvement; Solder Quality Score; Uniformity Statistic; Spatial Correlation; Dispersion Effects; Constrained Optimization.

1. INTRODUCTION

In the past many statisticians studying problems in industry have often been fortunate to have the benefit of an "ivory tower" research lab atmosphere available to conduct experiments. Unfortunately though, the techniques used for experimentation and decision making under this controlled scenario often are difficult to apply to a manufacturing process used for regular production. The nature of the process, in particular when one is dealing with a mature process, restricts the selection of design plans, levels of process variables, random replications and control over certain noise factors. Moreover, we have limited time to sample joint-quality measurements due to the requirement of work-in progress. The contents of this article will focus on a complete case study of a wave soldering process at Northern Telecom Inc. (NT) in the Research Triangle Park (RTP) in North Carolina. We will study the process from the definition of the wave soldering quality problem and its causes, to the development of quality measurements for the soldered joints on PCB's. These responses will be taken subject to the condition of the process variables for a particular run in a mixed–level fractional factorial experiment. Then the information obtained from characterizing the relationship between the quality measurements and the process variables will be used to determine the optimal process condition, which produces best PCB's and is insensitive to the environmental changes. Along the way, one must always remember that the experimental trials were conducted on a real manufacturing system and normal production was passing through the process while the experiment was in progress.

Over the past decade, there has been much interest in methods for designing and analyzing the results from experiments involving integrated circuit manufacturing. With discussion ranging from general algorithms for conducting a Taguchi-type (1980) experiment for a single response in surface mount technology by Bandurek, Disnet and Bendell (1988), to the effect of the spatial arrangement of integrated-circuits by Taam and Hamada (1990), to detailed case studies involving integrated circuit manufacturing

by Kackar and Shoemaker (1986). In studying multiple responses from integrated circuit experiments, Haigh and Logothetis (1988) considered the effect of each response on the process separately. They did not consider how to make an optimal decision for the process based on all responses. Lu, Mesenbrink and Gerig (1991) study the same plasma-etching data by taking into account the multivariate nature of the responses and by using a single objective function to handle this multi-objective problem. Literature involving the design and analysis of wave-soldering problems has been limited to the work done by Lin and Kackar (1989), Northern Telecom, and other telecommunications manufacturing companies. Shina (1991) studied the soldering problem through fitting linear models to counts of defects. Unfortunately, in studying a mature process, one only has a few defects ranging over a large number of experimental units, and methods like generalized linear models (c.f. McCullagh, 1980) or zero-influenced Poisson regression (c.f. Lambert, 1992) would be preferred. To prevent the loss of information from modeling count data, in this article, many representative joints are sampled and their solder qualities are classified into several categories. A scoring system that weights the ordered categorical values based on their distance away from the target is developed to transfer categorical data into continuous measurements for better modeling.

The data used in this study will be restricted to that which was obtained from a series of experiments performed on a certain class of PCB, assembled at NT's RTP facility. In section 2 we discuss the background of the wave soldering problem, define the quality characteristics and show how one obtains sampling information from such a process. A check-list was developed to reduce the effect of numerous noises such as dirty flux screen, incline of solder pot, etc. Section 3 will focus on the discussion of controllable variables, uncontrollable noises, the design of the experiment and all the differences that exist between running designed experiments in production systems and laboratories. Definitions of performance measurements such as the average and the

uniformity of bottom-side soldering qualities are provided and related to their roles in the process optimization procedure. The uniformity statistics take into account the spatial correlation that occurs between lead-quality measurements in the same type of components such as integrated circuits and PGA's. In Section 4, several regression functions with possible higher-order interactions between controllable variables are utilized to model the average, the uniformity and the dispersions of the responses. In Section 5 topside soldering quality, pre-soldering board temperature and dispersion effects are used as constraints for optimizing the average and uniform soldering-quality. A nonlinear programming method of constrained optimization is employed to determine the best and most robust parameter setting for the wave soldering process. The results from optimization will be studied through the confirmation experiments whose results will be discussed in section 6.

2. THE WAVE SOLDERING PROBLEM

The wave soldering process may be separated into three stages. Following the placement of components through the pinholes of the PCB, the boards travel down a conveyor belt at a designated speed, through an area where they are sprayed at a set velocity with flux, a resinous compound which when heated to at least 200°F will become adhesive, allowing for solder to stick to the leads on the board. For the flux to achieve this adhesive state, the boards must next travel through two preheat chambers, to activate the sticky nature of the flux. Following the preheating phase, the boards then travel through a pot of molten metal, i.e. solder, where the components are soldered to the boards.

The class of PCB's used in the study possess a network of pins or "leads" which protrude through the bottom-side of the boards from the various components located on the topside of the board (See Figure 1 for picture of test board). Upon examining this

class of circuit board, we identify five different types of leads. Looking at the boards with the long side being the top, the integrated circuit (IC) leads are found in vertical rows scattered throughout the board, the leads from a large square PGA circuit are in the right center of the board, the leads from a small PGA circuit are in left center of the board, hybrids or axials are scattered throughout the PCB, connector leads are found in two horizontal rows at the bottom of the board which serve as a directional guide when boards are placed on the conveyor belt. Altogether each PCB in the study contains 902 leads of these various classifications. Keeping the magnitude of this number in perspective with the sample board in Figure 1, each board measures 8.5″ × 13″ and the leads on the PGA sockets are only 30 mm apart thus leaving little space for error with respect to soldering a quality product.

(Please place Figure 1 and 2 here)

Because there are so many different types of PCB's in production, the process of obtaining the necessary stock of PCB's to conduct the experiment was laborious. The actual time of availability was unknown and the team needed to be prepared to run the experiment in the middle of the night. The main problem faced in the study dealt with maintaining the consistency of the nonmeasurable process variables of the system during the experiment, while not hindering the flow of normal production between different experimental runs. Experimental checklists were implemented in order to maintain the consistency of the process. Further comments on the issue will be addressed in Section 3.1 on experimental design.

All joints were inspected manually using a 10X ocular, and assigned a categorical value between "0" and "5" based on the quality characteristic created to measure the level of quality for each experimental unit sampled. Figure 2 explains how one may distinguish between the ordered categories. From past engineering experience, there exists a target amount of solder, category "3", that should appear on each joint of the board. An amount in excess of the acceptable range will cause a "short" between two

or more joints in a particular region. In contrast to this, if a lead receives an amount of solder that is less than the acceptable range, the solder deficiency, will prevent the flow of current at that particular site. Since there is no connection where the current may flow, the current will "skip" that particular site and cause the board to fail. So, we would like all joints on the board to have a similar (uniform) amount of solder that is as close to the target amount as possible.

At the time which the experiment was conducted, all data collection had to be performed manually, and due to a reduction in the level of work-in-progress allowed within the facility, all PCB's used in the experimental process needed to be shipped out within 36 hours of initial processing. This time constraint was one of the primary factors that needed consideration when a sampling scheme was determined. Recall that there are 902 possible experimental units on each PCB. Classifying soldering-quality into distinct categories like those shown on Figure 2 is extremely difficult, especially when one wants to limit measurement errors. Based on the past knowledge of engineers and operators involved with the process, certain leads of the different classifications were designated for sampling due to the knowledge of their prior repeated poor quality performance. Since many of the units sampled from the boards are less than 40 mm apart, there exists a strong spatial correlation pattern between those units sampled. In the development of performance measurements that describe uniformity between experimental units, we need to consider this correlation as well as the deviation in joint soldering-quality from the designated target value. Thus, keeping in mind these restrictions of time and necessity, it was decided by the engineers that a sample of size 40 would be representative of the level of quality from the joints on any particular PCB. The decomposition of those 40 units went as follows: 12 IC joints, 9 large PGA joints, 9 small PGA joints, 6 Hybrid joints and 4 Connector joints (see Figure 1 for location of sampled units); and given that 108 boards were used in the experimental study, this implies that 4320 experimental units were measured based on the quality characteristic

defined for all classifications of joints appearing on any particular PCB. Based on the sampling scheme above, after checking the correlation between soldered joints in different classifications we assume independence between strata, based on their spatial arrangement on any particular PCB. This will allow us to develop response variables to model each lead stratum univariately and avoid the complexities involved with fitting a multivariate linear model.

3. DESIGN OF EXPERIMENT AND PERFORMANCE MEASUREMENTS

Previous experimental studies conducted at NT failed to yield positive results with respect to improving the process due to the methodology that was used. Attempts were made to optimize the process using 2^k highly fractionated experiments to perform main effects analysis on ordered categorical quality measurements. Discussions with engineers and technicians told us why these experiments failed. For this manufacturing system, there exists multiple two- and three-factor interactions among linear and quadratic effects of the process variables. Such relationships could not be studied with the 2^{k-p} design that only examined linear main effects. Using this information, and the knowledge gained from cause-and-effect charts for the wave soldering process, we were convinced of the need to design a mixed-level fractional factorial experiment that would allow us to study the curvature and interaction relationships between the control variables.

3.1. Design Matrix Construction

Although several previous studies did not yield substantial improvement of the process, they did serve the purpose of reducing the size of the parameter space in need of examination. The eight important controllable variables that we will study are listed in Table 1. Factor **A** represents the temperature of the solder pot over which the PCB's travel to affix the components to the board. **B** and **C** are the temperatures of

the two preheat ovens where fluxed boards are heated to a specified temperature range which allows for the activation of the flux so that solder from the pot will stick to the leads. **D** specifies the speed at which PCB's travel on the conveyor belt through the system. **E** determines the velocity at which flux is applied to the boards. The more rpm's, the greater the amount of flux is applied to the board. **F** and **G** are vibration parameters which determine the depth at which boards may travel through the solder pot. **H** determines the order in which leads are soldered, at 0° the "Connector Leads" are soldered first, while at 180° the "Connector Leads" are soldered last.

(Please insert Table 1 here)

Unlike in a laboratory, where the noise variables introduced to the system might be controlled by the experimenter, vast noises will always exist in a real production system and thus precautions need to be taken to limit their influence over process quality. The grade of incline of the solder pot, clean flux screens, calibration of Ω and λ wave dials, closed wave trough, and regular removal of excess dross, are just a small segment of the "checklist" of those nonmeasurable factors which must be controlled in order to restrict their contribution to production noise or experimental error. Certain noise variables which influence the production system, cannot be controlled unless the process operates in a vacuum. Over time, the flux being used by the system, experiences a degradation process, which causes the viscosity of the flux to increase over time until the pH reaches a level which requires a titration that suggests that the compound no longer possesses its normal adhesive chemical properties. We regulated the pH level of the flux on an hourly basis to verify that the titration level remains within the allowable range of 17 to 21 drops to guarantee that the flux will maintain normal activity levels during the soldering phase. A titration level in excess of the 21 drop upper limit would create the need for the replacement of the flux and possibly repeating those experimental runs impacted by the out-of-control nature of this variable. Weather can influence the experimental results obtained. Changes in

humidity and barometric pressure, particularly when a study like ours is carried out over more than one day, can inflate the amount of noise influencing the production system. The use of a "Days" blocking variable would remove some of systematic noises. Although the "Days" effect is significant in this experiment, such a blocking variable cannot be utilized here. When we reach the process optimization stage of the study, the process is operated by three shifts, seven days a week. One would be unable to duplicate the exact weather conditions from any of days of the experiment. Hence determining those process conditions which are the most robust to changes in the environmental factors is a desirable process trait.

The wave soldering problem-charts that we studied allowed us to determine which controllable process variables needed to have an additional third medium level added to test for the possible higher-order effects that may influence the different response variables. Before the possible experimental levels for the process variables can be utilized, all possible treatment combinations must be checked for feasibility. For instance, all PCB's must be heated to a temperature between 200 and 230° F in order for proper flux activation to occur. The topside of the board needs to receive a sufficient amount of solder. The conveyor belt must travel at a speed sufficient to meet production quotas without sacrificing the quality of the product. Certain levels of a control variable by themselves may be feasible; but, due to the higher-order interactions which exist in this mature process, the combination of several levels of the control variables could lead to catastrophic results. As an example, if we have high levels of both Preheat temperatures, slow Conveyor Speed and high Drum Speed this will often lead to fires on the production line. After further examination, problems like this could lead to a reduction in the experimental range of controllable variables.

Based on the discussions held among team members and from the review of cause-and-effect diagrams, we made the decision to use the experimental layout given in Table 2 for a design $2^{3-1}3^{5-3}$ (L_{36} orthogonal array) of 36 runs (c.f. Phadke, 1989). Only

$3 + 2 \times 5 = 13$ degrees of freedom would then be needed to estimate all linear and quadratic components of the main effects. The L_{36} design was used to estimate all possible interactions that may influence the process, some of which are three factor interactions of quadratic effects. Since we are studying a matured production process, proper interpretation of these interactions are essential in statistical modeling. For example, the pre-soldering temperature of the circuit board is strongly influential in determining the solderability of the leads. Determining the best conditions to prevent these problems involves finding the best factor combination between Preheat 1, Preheat 2, Conveyor Speed and Drum Speed. Previous saturated main effect experimental studies failed to reveal any control variables that expressed a significant influence on soldering quality.

(Please insert Table 2 here)

Because we are experimenting on a real manufacturing system, by examining the design array in Table 2, we can see that the runs are ordered based on the degree of difficulty involved with changing between levels of the factors. For example, it may take as long as 90 minutes to change from the high to the low level of **A**. Thus, the runs need to be ordered such that the changes in **A** are minimized and limited to only factor level increases. Otherwise, not only will waiting time between experimental runs be increased; but, regular production will also lag behind normal levels. When small waiting times were unavoidable, accommodations needed to be made to allow for the running of normal production during the experimental study. Due to the set up time involved in using one of NT's normal production lines, the experiment was carried out in two days, with 18 trials carried out on each day. Traditional replication of design points was not feasible, so each design point was repeated 3 times sequentially, and normal production flowed through the process between each execution of a triplet of PCB's. No significant autocorrelation existed among the residuals, despite the sequential execution of a triplet of PCB's.

3.2. Response Variables or Performance Measurements

There are four primary groups of response variables involved in the study: (1) **Bottom-Side Soldering Quality** (BSSQ) is characterized by a Mean Solder Quality Score (MSQS), which measures the average quality level between units within a particular type of lead, and a Uniformity statistic, which measures the degree of mismatch between sampled units from a particular component; (2) **Topside soldering quality** is determined by the number of insufficiently filled pinholes on the topside of the PCB's; (3) **Pre-soldering Board Temperature** has to reach 200 to 230°F for proper flux activation to occur; **(4) Dispersion** measures the variation in the manufacturing system between the different replications for both MSQS and uniformity statistics. In total, there will be 22 response values for each design point. Each of the five lead classifications has its own MSQS and uniformity statistics with a corresponding dispersion measurement for each of the BSSQ measurements.

3.2.1. Bottom–side Soldering Quality Measurement

Data measurements are assigned ordered categorical values based on the angle made when solder sticks to the lead as shown in Figure 2. Previous work done to handle ordered categorical data is extensive, see Box (1986), Nair (1986), and Hamada and Wu (1990) for references. After discussions with engineers, it was suggested that to distinguish between the ordered categories, we should weight those ordered categories farther away from the target more heavily so that those joints with lesser quality will have a greater impact on the results obtained from the experimental data. The MSQS response, $\bar{x}_{ikl} = \Sigma_{j=1}^{n_i} x_{ijkl} / n_i$ which measures the average solder quality score for all leads sampled, are given in Table 3a with a target value T = 1.0. For measuring the uniformity of the soldered joints, we define the deviation to target $Z_{ijkl} = X_{ijkl} - T$ for the *jth* soldered joint, in the *ith* classification, of the *lth* repetition of run k, where $i = 1, 2, \ldots, 5$, $k = 1, 2, \ldots, 36$, $l = 1, 2, 3$. Next we compute the variance for each

paired difference of absolute deviations of soldered joints (j, h) sampled within each stratum i, i.e. component type, which gives the magnitude of the mismatch between two soldered joints as $\mathrm{var}\left(Z_{ijkl} - Z_{ihkl}\right)$. This is similar to the variogram used in spatial statistics (c.f. Cressie, 1991 page 58). The uniformity statistic u_{ikl} is defined as

$$u_{ikl} = \left(n - 1\right) * \Sigma_{j=1}^{n_i} \mathrm{var}\left(Z_{ijkl}\right) - 2 * \Sigma_{j>h}^{n_i} \mathrm{cov}\left(Z_{ijkl}, Z_{ihkl}\right).$$

This allows us to reduce the 4320 observations collected from every sampled joint, to a problem with five response variables consisting of 108 observations, from 36 design points sequentially repeated 3 times. See Table 3b for its summary statistics. If all the sampled units within a particular strata were judged to have excess solder, i.e. a score of 150, since they were all uniform, this implies $u_{ikl} = 0$. For this reason, we also require that MSQS be made closely to target T simultaneously.

(Please insert Table 3a and 3b here)

3.2.2. Topside Soldering Measurement and Pre-soldering Board Temperature

All topside sites with insufficiently filled pinholes were counted and recorded for every experimental unit. After plotting the residuals of regression modeling of counts over the experimental runs and noticing nothing unusual in the randomness and normality of residuals, we assume that the occurrence of such events approximately follows a normal distribution. Temperature gauge stickers with ranges between 180 and 260° F are placed on the center of every PCB prior to their entry into the production system. The temperature of the board to the nearest 5° F is recorded at the moment immediately preceding the PCB's entry into the solder pot. Only four variables Preheat 1, Preheat 2, Conveyor Speed and Drum Speed are needed to characterize the relationship between the pre-soldering temperature and performance measurements collected from the production process. The modeling of the defective pinholes and the pre-soldering board temperature serves as a physical restriction on the quality of the output produced by the process.

3.2.3. Dispersion Measurements

Dispersion responses are used to measure the pure error, i.e. noise, not detected by location response measurements like the uniformity statistic and mean solder quality score. By modeling dispersions we can determine optimal process conditions under which the influence of noise on the quality of the product is minimized, i.e. find the process recipe which is robust to environmental changes. The modeling of dispersion due to uniformity and MSQS is utilized as a system of constraints in the optimization of bottom-side solder quality. This concept is different to Taguchi's (1980) signal-to-noise ratio methodology and is most recently discussed by Vining and Myers (1990) as a dual response approach to optimize both location and dispersion effects. As well, Box and Meyer (1986) for unreplicated experiments, and Freeny and Nair (1991) for replicated cases, provide more detailed discussion on the utilization of dispersion measurements. For our study we have two sets of five dispersion response variables, such that each joint sampled within strata i has a dispersion measurement due to uniformity to target, and a dispersion measurement due to the mean solder quality score. Thus the measurements from each set may be defined by $s^2_{u_{ik}} = \Sigma^3_{l=1}\left(u_{ikl} - \bar{u}_{ik.}\right)^2$ and $s^2_{\bar{x}_{ik}} = \Sigma^3_{l=1}\left(x_{ikl} - \bar{x}_{ik.}\right)^2$, $k = 1, \ldots, 36$.

4. MODEL BUILDING: A TOOL FOR OPTIMIZATION

Based on the information obtained through discussion with engineers and studying the performance of the wave soldering process during normal production we were able to specify a substantial set of possible interactions. These higher-order effects were included in the fitting of a preliminary 32-term polynomial regression model for the sets of BSSQ response measures shown in Table 4. The purpose of fitting such models was to develop a baseline prediction function which can be used to check for diagnostics of the residuals like unequal variances, autocorrelation, and lack of fit. This will allow for the best set of transformations of response variables to be determined.

Then once stability of the residuals had been achieved, both forward and backward stepwise regressions are used to determine lower and upper bounds on the number of model terms to be considered. Afterwards, all-subsets regression is employed to choose the best model to explain each of the 22 different functional relationships. The maximum adjusted R^2 is used as the criterion for choosing the best subset model. The model parameters from each "best" subset were then used in an optimization algorithm to find the best process recipe. Any reduction of unnecessary model terms will decrease the computational time required during the optimization phase.

(Please insert Table 4 here)

4.1. Transformation Selection and Residual Diagnostics

The two areas of primary focus when carrying out residual diagnostics involve checking whether our errors are normally distributed with constant variance. Normal probability plots of the model errors before and after transformation fail to show any signs of nonnormality. Examination of the predicted versus residual plots in Figure 3 for the BSSQ response variables clearly show the possible presence of a nonconstant variance relationship for our respective response variables. The Box-Cox transformation is employed to stabilize the variances. We shift u_{ikl} by a positive constant, e.g. $u'_{ikl} = u_{ikl} + 1$, to prevent the nonexistence of certain observations when $u_{ikl} = 0$ in transformations. The $\log_e$ transformation is a satisfactory variance stabilizer (see Table 5) for most of the MSQS and the uniformity statistics, except for u'_{2kl} where $\lambda = -0.2$. In this particular case the sensitivity of changing the transformation parameter from $\lambda = 0.0$ to -0.2 is extensive. From the results in Table 5 and 6 one can see that for a $\log_e$ transformation the lack of fit statistic for the model with $i = 2$ is significant at $\alpha = 0.05$, while the p–value for the lack of fit statistic for $\lambda = -0.2$ is 0.3190. Figure 3 shows an example of the effects of the variance-stabilizing transformations on the residuals.

(Please insert Table 5, 6 and Figure 3 here)

Although Box–Cox transformations removed the unequal variance problem, the predicted versus residual plots for the transformed BSSQ response measures in Figure 3 show somewhat of a linear pattern persisting among the residuals. Based on an explanation due to Searle (1989), this can be attributed to the substantial number of identical values that exist among the response measures u'_{ikl} and $\bar{x}_{ikl}$. This is a result of the change made from an ordered categorical to a pseudo–continuous response measure. Nothing can be done to amend this problem. Thus, the need exists for advances in technology, such as X-ray inspection machine, which will allow for collecting continuous measurements for better modeling.

Despite the implementation of checklists to limit the influence of noises on the manufacturing system, the maximum amount of explainable variation (R-Square) for any of the BSSQ response variables, is 58.56% for mean response $\bar{x}_{2kl}$. However, the modeling of the dispersion effects due to the mean and the uniformity statistics was able to explain the contributions to noises. The "worst case" model fit to the dispersion measurements possessed an $R^2 = .5300$. Examining the summary of variable selections for BSSQ measurements in Table 7 we see the differences in the model for the different groups of response variables through the vast range of parameters that are necessary for the various models. Studying the detailed summaries provided in Tables 8 – 11 for the Large PGA models shows the importance of studying higher-order interactions for characterizing the best operating conditions. Since the interactions make up the majority of the highly significant terms in the models, the failure to include these terms in the models could possibly have led to uninformative or perhaps incorrect decisions in the optimization phase, which is the reason why previous engineering attempts did not succeed to improve quality of the process.

(Please insert Tables 8–11 here)

5. PROCESS OPTIMIZATION

The goal of our wave soldering optimization algorithm is to create an objective function that simultaneously minimizes the uniformity statistic and the mean solder quality score subject to the constraints in Section 3.2.2 and 3.2.3. Since all work involves a real production system, we need to guarantee that the solution can be implemented smoothly on the process. Note that the control variables which include both continuous and discrete variables and their functional relationships to the averages, uniformities and dispersions are highly non-linear.

The projected lagrangian algorithm by Robinson (1972) available in the General Algebraic Mathematical Solver (GAMS), was found to be quite capable of handling this non-linear constrained optimization problem. This algorithm operates through a sequence of iterations where each iteration involves linearization of nonlinear functions and solving the resulted linearly constrained subproblem. To improve the chances of obtaining an optimal feasible solution from the model in this form, the regression parameter estimates need to be transformed to the same scale. For example, the parameter estimates of u_{2kl}, which required a Box-Cox transformation of $\lambda = -0.2$, need to be transformed back to the original scale and taken $\log_e$'s. This allows each part of the objective function to have equal weight. To prevent the iterative search procedure from heading directly to the boundaries as a solution for the control variables, initial values must be given for each control variable. We randomly selected 100 combinations of initial values for the control variables within the experimental range to use in solving the nonlinear system of equations. The more repetitions that we see among the locally optimal solutions produced by the algorithm, gives an idea of the model's stability as a good predictor of the optimal operating conditions of the process. Through the set of initial values that were run through the program, only four locally optimal solutions were repeated among the 100 different possible sets of the algorithm (see Table 12). These sets of locally optimal solutions were then used to conduct a confirmation

experiment to determine the optimal operating conditions for the wave soldering process under normal production.

(Please insert Table 12 here)

6. CONFIRMATION OF SOLUTIONS FROM OPTIMIZATION

Due to high degree of nonlinearity in the feasible region for the wave solder process improvement problem, no global optimal solution could be found, so the best recipe needed to be chosen from the set of locally optimized solutions given in Section 5. To make this decision, 10 PCB's were run through the process at each of the solutions in Table 12 and then this process was repeated with another 10 PCB's except in the reverse order to limit the waiting needed for changing the levels of control variables. To assure the validity of these results, the experimental checklist, employed in Section 3, was used to check and make sure that nonmeasurable process variables were in the same state as during the original mixed–fractional factorial experiment.

In order to determine which optimal solution produces the greatest process improvement, we compute the average of MSQS and uniformity statistics from all 40 sampled-leads on each board in 20 PCB's examined, so that one grand uniformity statistic and one MSQS are obtained for one optimal solution. By comparing all these summary statistics, we conclude that the solution 2 provides the greatest level of improvement for the process. Examining the results of the sample taken prior to experimentation with the results from the best confirmation solution in Table 13 and 14, we observe a grand uniformity statistic of 0, *i.e.* totally uniform joints (with the exception of one outlier) and a 32.85% decrease in the grand mean solder quality score. This figure may be conservative considering that the pre-experimentation samples were taken after board repair; so a 10% defect rate would inflate the saving achieved even further. Some of the soldering-quality fell into the category "2" mainly because the suggested process recipe was aimed to produce good quality joints consistently for a long

period.

(Please insert Table 13 and 14 here)

Finally, in order to guarantee the longevity of the chosen optimal solution we suggest the utilization of some form of on-line process control to continually monitor the performance of the selected optimal solution. Without this in place, the improved quality achieved by the recommended process setting will be short-lived because operators usually make changes according to their judgment from time to time, especially when they are facing assignable causes of process failures. After the success of this study, many NT's production systems are improved by following the methodology presented in this article. In particular, a quality-team has reported an improvement of a multi-layer process by at least 300% and the saving of rework is invaluable there.

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Table 1. Controllable Process Variables

Variables	*Levels*
A = Solder Pot Temperature	470° F, 490° F, 510° F
B = Preheat 1 Temperature	650° F, 750° F, 850° F
C = Preheat 2 Temperature	650° F, 750° F, 850° F
D = Conveyor Speed	4 fpm, 5.5 fpm, 7.0 fpm
E = Drum Speed	3.0 rpm, 7.5 rpm
F = Ω Wave Setting	0.10, 0.25, 0.40
G = λ Wave Setting	2.5, 3.5
H = Board Direction	0°, 180°

Table 2. L_{36} Orthogonal Design Array

Trial	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*
1	470	650	650	4.0	3.0	0.10	2.5	180
2	470	650	750	5.5	3.0	0.10	3.0	0
3	470	650	650	5.5	7.5	0.40	2.0	0
4	470	650	650	7.0	7.5	0.25	3.5	180
5	470	750	750	5.5	3.0	0.25	2.5	180
6	470	750	850	7.0	3.0	0.25	3.5	0
7	470	750	750	7.0	7.5	0.10	2.5	0
8	470	750	750	4.0	7.5	0.40	3.5	180
9	470	850	850	7.0	3.0	0.40	2.5	180
10	470	850	650	4.0	3.0	0.40	3.5	0
11	470	850	850	4.0	7.5	0.25	2.5	0
12	470	850	850	5.5	7.5	0.10	3.5	180
13	490	650	850	5.5	3.0	0.10	2.5	180
14	490	650	850	7.0	7.5	0.40	2.5	0
15	490	650	850	4.0	7.5	0.40	3.5	180
16	490	650	650	4.0	3.0	0.25	3.5	0
17	490	750	650	7.0	3.0	0.25	2.5	180
18	490	750	750	5.5	3.0	0.40	3.5	0
19	490	750	650	4.0	7.5	0.10	2.5	0
20	490	750	650	5.5	7.5	0.10	3.5	180
21	490	850	750	4.0	3.0	0.40	2.5	180
22	490	850	850	7.0	3.0	0.10	3.5	0
23	490	850	750	5.5	7.5	0.25	2.5	0
24	490	850	750	7.0	7.5	0.25	3.5	180
25	510	650	750	7.0	3.0	0.10	2.5	180
26	510	650	750	4.0	3.0	0.25	3.5	0
27	510	650	750	7.0	7.5	0.40	2.5	0
28	510	650	850	5.5	7.5	0.25	3.5	180
29	510	750	850	4.0	3.0	0.25	2.5	180
30	510	750	850	5.5	3.0	0.40	3.5	0
31	510	750	850	4.0	7.5	0.10	3.5	0
32	510	750	650	7.0	7.5	0.40	2.5	180
33	510	850	650	5.5	3.0	0.40	2.5	180
34	510	850	650	7.0	3.0	0.10	3.5	0
35	510	850	650	5.5	7.5	0.25	2.5	0
36	510	850	750	4.0	7.5	0.10	3.5	180

Note: Each experimental run was repeated three times in succession during the experiment.

Table 3a. Mean Solder Quality Score Summary Statistics

	$\bar{x}_{1.kl}$		$\bar{x}_{2.kl}$		$\bar{x}_{3.kl}$		$\bar{x}_{4.kl}$		$\bar{x}_{5.kl}$	
Run	Mean	Var	Mean	Var	Mean	Var	Mean	Var	Mean	Var
1	1.0233	0.1130	1.4266	0.1003	1.4848	0.1248	1.7885	0.0893	0.3662	0.4023
2	1.2406	0.2411	1.8060	0.9721	1.2980	0.0345	0.7324	0.4023	0.6931	0
3	1.2841	0.0441	2.0904	1.6507	0.4527	0.6148	1.2800	0.0122	1.3273	0.1084
4	1.5544	1.0483	0.7902	0.0713	0.2310	0.1602	1.1527	0	0.5973	0.3086
5	0.8555	0.1755	0.7102	0.4077	0.8931	0.0496	0.5649	0.2393	0.4823	0.6979
6	1.5429	0.0017	2.8558	2.4556	0.8670	0.1602	1.1527	0	0.5973	0.3086
7	1.2689	0.0443	3.6926	0.0502	1.3161	0.0399	0.9541	0.2552	0.4621	0.1602
8	0.8797	0.1044	0.2120	0.1348	0.9318	0.0660	0.9163	0	0	0
9	0.8306	0.0884	0.2310	0.1602	0.5847	0.0353	0.7385	0.4457	0.6239	0.3509
10	1.1296	0.0166	0.2824	0.2393	0.5716	0.2720	1.3658	0.6551	0.2310	0.1602
11	0.9088	0.6448	0.8400	0.3611	0.8283	0.5353	1.1243	0.1299	0.2310	0.1602
12	1.0582	0.0376	0.2310	0.1602	0.8634	0.5977	0.9415	0.2349	0.2310	0.1602
13	0.6641	0.1316	0.5973	0.3086	0.4621	0.1602	0.5365	0.3022	1.0796	0.1423
14	1.1803	0.1844	2.6383	1.3222	0.8283	0.5353	1.3297	0.1602	0.4621	0.6406
15	1.9194	0.8571	0.7306	0.4058	0.4430	0.1480	0.7811	0.0548	1.0986	0
16	1.0696	0.0025	0.3536	0.1203	0.6741	0.4815	1.4799	0.0352	0.4621	0.6406
17	1.1518	0.0802	0.1226	0.0451	1.0425	0.2283	0.8189	0.0870	0.2310	0.1601
18	1.0634	0.0205	0.2310	0.1602	1.2810	0.0252	0.6230	0.0377	0	0
19	1.1296	0.0166	1.2296	2.4595	0.1226	0.0451	1.1486	0.0681	0.6239	0.3509
20	0.7585	0.0460	0.2310	0.1602	0.8283	0.0548	0.9100	0.6215	0	0
21	0.5632	0.3494	0	0	0	0	0	0	0	0
22	1.0617	0.0269	0.2310	0.1602	0	0	0.6034	0.4285	0.3929	0.4631
23	1.0892	0.2667	1.6292	2.7925	0.3536	0.3751	1.1851	0.1508	0	0
24	1.2238	0.0607	0.2310	0.1602	0	0	1.2901	0.4749	0.8752	0.5925
25	1.0739	0.0186	0.2451	0.0451	0.5973	0.3086	1.6333	0.0259	0	0
26	1.2735	0.0788	0.8915	0.6957	0.7836	0.0433	1.4663	0	0.3929	0.4631
27	1.2901	0.0485	1.5877	1.3629	0.6451	0.4221	1.2881	0.0339	0.9444	0.1894
28	0.9964	0.0150	0.5649	0.2393	0.4944	0.1945	1.1365	0.9687	0.3662	0.4023
29	1.0508	0.1144	1.2459	2.2077	0.9242	0.6406	1.8876	0.0035	0	0
30	0.7838	0.0788	0	0	1.1432	0.0443	1.1337	0.4111	0.2310	0.1602
31	1.1262	0.0259	0.4944	0.1945	0.5973	0.3086	0.9415	0.2349	0.3929	0.4631
32	0.8154	0.0929	0.3536	0.1203	0.4888	0.3127	1.5041	0.1120	0	0
33	1.7634	1.0332	0	0	1.3573	0.0603	1.5253	0.2099	0.2310	0.1602
34	0.4621	0.1602	2.2820	4.1579	0.9242	0.6406	0.6486	0.3313	0.3662	0.4023
35	0.5135	0.2037	0.2120	0.1348	0.4621	0.6406	0.8676	0.6056	0.3929	0.4631
36	0.7385	0.0642	0.4888	0.3127	0.4972	0.7417	1.2579	0.1637	0	0

Table 3b. Uniformity To Target Summary Statistics

Run	$u_{1.kl}$		$u_{2.kl}$		$u_{3.kl}$		$u_{4.kl}$		$u_{5.kl}$	
	Mean	Var	Mean	Var	Mean	Var	Mean	Var	Mean	Var
1	6.1524	1.3726	0.0182	0.000019	6.6815	0.0865	5.7910	0.1938	0.9883	2.9300
2	5.4260	0.9131	0.0187	0.000036	6.4232	0.1188	2.5172	4.7520	2.6771	0
3	6.1992	0.9649	0.0155	0.000080	2.1872	14.3516	5.4818	0.0017	4.4490	1.6728
4	8.5725	10.8639	0.0247	0.000041	2.0209	12.2517	5.5288	0	1.8806	2.6733
5	5.7588	1.0535	0.0224	0.000105	4.6440	0.0565	2.4386	4.4602	1.6434	8.1027
6	5.6605	0.8871	0.0134	0.000199	4.9445	0.9913	5.3586	0.1393	1.8806	2.6733
7	5.6729	0.8271	0.0049	1.22E-11	6.6817	0.0240	4.0608	1.2760	1.7847	2.3890
8	5.5477	1.3481	0.0313	0.000025	5.7290	1.4822	5.5581	0	0	0
9	5.3800	0.8723	0.0287	0.000088	5.3058	1.7181	3.0720	7.9866	2.5748	6.3766
10	5.1339	0	0.0313	0.000025	3.6856	10.7462	3.8914	1.4846	0.8924	2.3890
11	4.0676	13.3452	0.0240	7.441E-6	4.5492	15.5324	5.6817	0.0458	0.8924	2.3890
12	5.5240	0.5349	0.0341	8.213E-15	4.4945	15.1637	3.3446	0.0736	0.8924	2.3890
13	5.0860	1.5109	0.0287	0.000087	4.1127	12.6973	2.3122	4.1274	3.5241	1.5038
14	6.1473	1.2190	0.0145	0.000094	4.5185	15.3355	4.3812	1.0996	0.8924	2.3890
15	8.5845	9.3648	0.0268	0.000044	3.4774	9.7859	4.7680	1.8725	2.9648	0
16	5.5771	0.5169	0.0313	0.000025	3.7661	12.2744	4.2118	1.9221	0.8924	2.3890
17	6.6420	0.1768	0.0313	0.000025	5.8746	1.0011	3.5405	0.0967	0.8924	2.3890
18	5.5445	0.5059	0.0341	8.213E-15	6.7057	0.0383	3.3446	0.0736	0	0
19	5.1339	0	0.0271	0.000150	1.2641	4.7938	3.6579	0	2.5748	6.3766
20	5.7938	1.1156	0.0341	8.213E-15	6.3524	0.1122	3.8288	11.0758	0	0
21	3.9396	13.4227	0.0341	0	0	0	0	0	0	0
22	5.5665	0.5258	0.0287	0.000087	0	0	2.2820	3.9607	1.6824	8.4916
23	6.0609	1.6642	0.0218	0.000214	2.0328	12.3963	2.4779	4.6084	0	0
24	6.6842	0.0739	0.0287	0.000087	0	0	5.0327	2.5529	3.3259	8.2994
25	6.9249	0.0003	0.0284	0.000025	4.2606	13.7221	5.9463	0.0009	0	0
26	4.7182	0.4147	0.0246	0.000076	5.0712	0.7795	3.1879	0	1.6824	8.4916
27	5.1684	1.4632	0.0231	0.000077	3.0544	7.0419	3.5405	0.0967	3.4282	1.6923
28	5.9775	0.5338	0.0272	0.000037	3.0047	6.7898	4.0972	12.5906	0.9883	2.9300
29	6.3471	0.0072	0.0275	0.000035	4.6190	16.0014	5.8294	0.0173	0	0
30	5.4610	0.6689	0.0341	0	5.4970	1.5369	4.1852	1.5706	0.8224	2.3890
31	5.1134	0.0038	0.0292	0.000034	4.3316	14.1211	3.3446	0.0736	1.6824	8.4916
32	6.5485	0.1012	0.0259	0.000066	3.5038	11.3490	5.8129	0.0612	0	0
33	8.2975	11.0268	0.0341	0	6.8052	0.0120	5.7670	0.0627	0.8924	2.3890
34	3.2496	7.9197	0.0173	0.000023	4.6190	16.0014	2.4779	4.6084	0.9883	2.9300
35	3.3062	8.2054	0.0313	0.000025	2.3095	16.0014	3.0375	7.5288	1.6824	8.4916
36	5.2853	0.9667	0.0259	0.000066	2.2855	15.6706	5.7443	0.1212	0	0

Table 4. Baseline Preliminary Model

$$
\begin{aligned}
Y_{ikl} \;=\; & \beta_1 A + \beta_2 A^2 + \beta_3 B + \beta_4 B^2 + \beta_5 C + \beta_6 C^2 + \beta_7 D + \beta_8 D^2 \\
& + \beta_9 E + \beta_{10} AE + \beta_{11} A^2 E + \beta_{12} BE + \beta_{13} B^2 E + \beta_{14} CE + \\
& + \beta_{15} C^2 E + \beta_{16} BD + \beta_{17} BD^2 + \beta_{18} B^2 D + \beta_{19} B^2 D^2 + \\
& \beta_{20} CD + \beta_{21} CD^2 + \beta_{22} C^2 D + \beta_{23} C^2 D^2 + \beta_{24} DE + \beta_{25} D^2 E \\
& + \beta_{26} AC + \beta_{27} AC^2 + \beta_{28} A^2 C + \beta_{29} A^2 C^2 + \beta_{30} F + \beta_{31} F^2 + \\
& \beta_{32} G + \beta_{33} H + \epsilon_{ikl}, \quad i = 1, \ldots, 5,\ k = 1, \ldots, 36,\ l = 1, 2, 3.
\end{aligned}
$$

Table 5. Lack of Fit for Transformed Uniformity Model

Response Area	λ	*SSPE*	*SSLOF*	*F-value*	*p-value*
I.C.'s	$\log_e$	188.6622	4.36313	0.41628	0.79637
Large PGA	-0.2	0.00420	0.0002128	1.21371	0.31908
Small PGA	$\log_e$	519.9698	34.32779	1.18834	0.32329
Hybrids	$\log_e$	157.0590	11.35408	1.30125	0.27775
Connectors	$\log_e$	207.2564	15.10877	1.31218	0.27366

Table 6. Lack of Fit for u'_{2kl} for Different Transformation Parameters λ's

λ	*SSPE*	*SSLOF*	*F-value*	*p-value*
-03	0.0002124	1.54125E-05	1.305913	0.27596
-0.2	0.004207	0.0002128	1.21370	0.31098
-0.1	0.052534	0.0042819	1.95614	0.12825
$\log_e$	307.8162	39.517795	3.08115	0.03272
0.1	219.3712	40.846367	4.46874	0.00619

Table 7. Bottom Side Soldering Quality Model Summary

	Model			
	Uniformity	*Mean Quality Score*	*Mean Dispersion*	*Uniformity Dispersion*
Strata	R^2	R^2	R^2	R^2
	# Parameters	*# Parameters*	*# Parameters*	*# Parameters*
I.C.	.3932	.3864	.8748	.9984
	16	16	15	29
Large PGA	.5078	.6042	.6571	.8431
	19	23	14	17
Small PGA	.3738	.3662	.8870	.8577
	32	15	23	18
Hybrids	.5212	.4820	.6592	.6237
	22	16	12	13
Connectors	.4026	.3220	.6179	.7390
	32	13	11	14

#: No. of parameters

Table 8. Summary of Modeling Uniformity Statistic For Large PGA

Parameter	*Estimate*	*Std. Error*	*t–statistic*	*p–value*
A	0.001894	0.0008786	2.16	0.0339
A^2	-0.001207	0.0004887	-2.47	0.0155
E	-0.001479	0.0007087	-2.09	0.0398
A^2E	0.001404	0.0005133	2.73	0.0076
B	0.004881	0.0012918	3.78	0.0003
C^2	0.001097	0.0052953	2.07	0.0412
AC	0.002631	0.0013793	1.91	0.0597
AC^2	-0.001174	0.0006709	-1.75	0.0836
A^2C	0.001123	0.0006373	1.76	0.0815
A^2C^2	-0.000805	0.0004671	-1.72	0.0884
BE	0.002997	0.0012235	2.45	0.0163
B^2E	-0.001159	0.0005668	-2.05	0.0438
C^2E	0.001098	0.0005528	1.99	0.0502
D^2	-0.001257	0.0005835	-2.15	0.0339
F	0.004991	0.0011919	4.19	0.0001
BD^2	-0.000917	0.0006830	-1.34	0.1829
B^2D	0.001769	0.0006804	2.60	0.0109
G	0.001996	0.0007219	2.76	0.0069
H	0.002651	0.0006957	3.81	0.0003

$R^2 = .5078$

Table 9. Summary of Modeling Mean Solder Quality Score For Large PGA

Parameter	*Estimate*	*Std. Error*	*t–statistic*	*p–value*
E	0.164964	0.084431	1.95	0.0541
A	-0.219960	0.981203	-2.24	0.0276
A^2	0.084910	0.055788	1.52	0.1318
AE	-0.126272	0.098121	-1.29	0.2017
A^2E	-0.222842	0.059366	-3.75	0.0003
B	-0.749403	0.168590	-4.45	0.0001
B^2	-0.130016	0.065220	-1.99	0.0495
C^2	-0.152981	0.061700	-2.48	0.0152
AC	-0.648719	0.208024	-3.12	0.0025
A^2C	-0.093024	0.082528	-1.13	0.2629
A^2C^2	0.122327	0.058658	2.09	0.0401
BE	-0.671173	0.156315	-4.29	0.0001
B^2E	0.175011	0.067160	2.61	0.0108
C^2E	-0.236269	0.068218	-3.46	0.0008
D	-0.200206	0.133678	-1.50	0.1380
F	-0.837294	0.155958	-5.37	0.0001
BD^2	0.115910	0.080485	1.44	0.1535
B^2D	-0.137961	0.080454	-1.71	0.0901
B^2D^2	-0.053890	0.049618	-1.09	0.2805
C^2D	0.108381	0.081961	1.32	0.1896
DE	0.237590	0.128015	1.86	0.0670
G	-0.231346	0.091003	-2.54	0.0129
H	-0.458653	0.079336	-5.78	0.0001

$R^2 = .6042$

Table 10. Summary of Modeling Dispersion Due To Uniformity Statistic For Large PGA

Parameter	*Estimate*	*Std. Error*	*t–statistic*	*p–value*
A	-0.0000596155	0.00001796	-3.32	0.0038
A^2E	0.0000387451	0.00000917	4.22	0.0005
A^2G	-0.0000306726	0.00001067	-2.87	0.0101
AC	0.0000618131	0.00002351	2.63	0.0170
BE	0.0001001844	0.00002119	4.73	0.0002
CE	-0.0000336270	0.00001667	-2.02	0.0588
C^2E	-0.0000237303	0.00000847	-2.80	0.0118
F	0.0000218659	0.00001860	1.18	0.2551
D	0.0000392457	0.00001707	2.30	0.0337
D^2	0.0000196793	0.00000897	2.19	0.0417
BD^2	-0.0000398646	0.00001160	-3.44	0.0029
B^2D	0.0000383617	0.00001170	3.28	0.0042
C^2D	0.0000364439	0.00001376	2.65	0.0163
DE	-0.0000631677	0.00001656	-3.81	0.0013
D^2E	-0.0000301669	0.00000849	-3.55	0.0023
A^2D^2	-0.0000302665	0.00000598	-5.06	0.0001
BC	-0.0001167210	0.00002648	-4.41	0.0003

$R^2 = .8431$

Table 11. Summary of Modeling Dispersion Due To Mean Score For Large PGA

Parameter	*Estimate*	*Std. Error*	*t–statistic*	*p–value*
A^2	0.201602	0.190191	1.06	0.2990
A^2E	0.864156	0.214431	4.03	0.0006
BE	0.823619	0.355008	2.32	0.0305
CE	-1.040408	0.346802	-3.00	0.0068
C^2E	-0.401058	0.202554	-1.98	0.0611
BD^2	-0.455321	0.240911	-1.89	0.0724
B^2D	0.384867	0.242055	1.59	0.1274
B^2D^2	0.302619	0.149073	2.03	0.0550
C^2D^2	0.299460	0.149730	2.00	0.0581
DE	-0.460574	0.322150	-1.43	0.1688
DE^2	-0.344339	0.198123	-1.74	0.0969
AD^2	-0.367244	0.249737	-1.47	0.1562
A^2D^2	-0.589288	0.143315	-4.11	0.0005
BC	-1.195812	0.485216	-2.46	0.0224

$R^2 = .6571$

Table 12. Locally Optimal Solutions Obtained Through Nonlinear Constrained Optimization

Control Variable	*Solution*			
	1	*2*	*3*	*4*
Solder Pot Temperature	472°F	486°F	489°F	484°F
Preheat 1	650°F	833°F	749°F	718°F
Preheat 2	706°F	758°F	666°F	700°F
Conveyor Speed	4.00 fpm	5.41 fpm	4.56 fpm	4.53 fpm
Drum Speed	7.00 rpm	5.47 rpm	7.50 rpm	7.50 rpm
Ω	0.26	0.17	0.20	0.19
λ	2.7	2.5	2.5	3.0
Board Direction	0°	0°	0°	0°

Table 13. Before Optimization

	Categories			
Board	*1*	*2*	*3*	*4*
1	0	20	20	0
2	0	24	15	1
3	0	22	18	0
4	0	22	17	1
5	1	22	17	0
6	3	20	17	0
7	0	21	18	1
8	0	19	21	0
9	0	21	18	1
10	2	22	16	0
11	1	23	14	2
12	3	19	15	3
13	0	20	17	3
14	0	21	16	3
15	0	26	14	0
16	0	26	14	0
17	2	26	10	2
18	0	21	18	1
19	1	21	18	1
20	3	17	19	1
Total	16	432	333	19

Grand Mean Score =
2843/800 = 3.553750

Total Uniformity Statistic = 14,911.1232

Table 14. Performance of Best Control Settings After Optimization

	Categories				
Board	*1*	*2*	*3*	*4*	*5*
1	0	12	28	0	0
2	0	12	28	0	0
3	0	12	28	0	0
4	0	12	28	0	0
5	0	12	28	0	0
6	0	12	28	0	0
7	0	12	28	0	0
8	0	12	28	0	0
9	0	12	28	0	0
10	0	12	28	0	0
11	0	12	27	0	1
12	0	12	28	0	0
13	0	12	28	0	0
14	0	12	28	0	0
15	0	12	28	0	0
16	0	12	28	0	0
17	0	12	28	0	0
18	0	12	28	0	0
19	0	12	28	0	0
20	0	12	28	0	0
Total	0	240	559	0	1

Note: Grand mean score = 1909/800 = 2.38625;
% decrease mean score after optimization = 32.85%;
Total uniformity statistic = 0 if 1 outlier deleted.

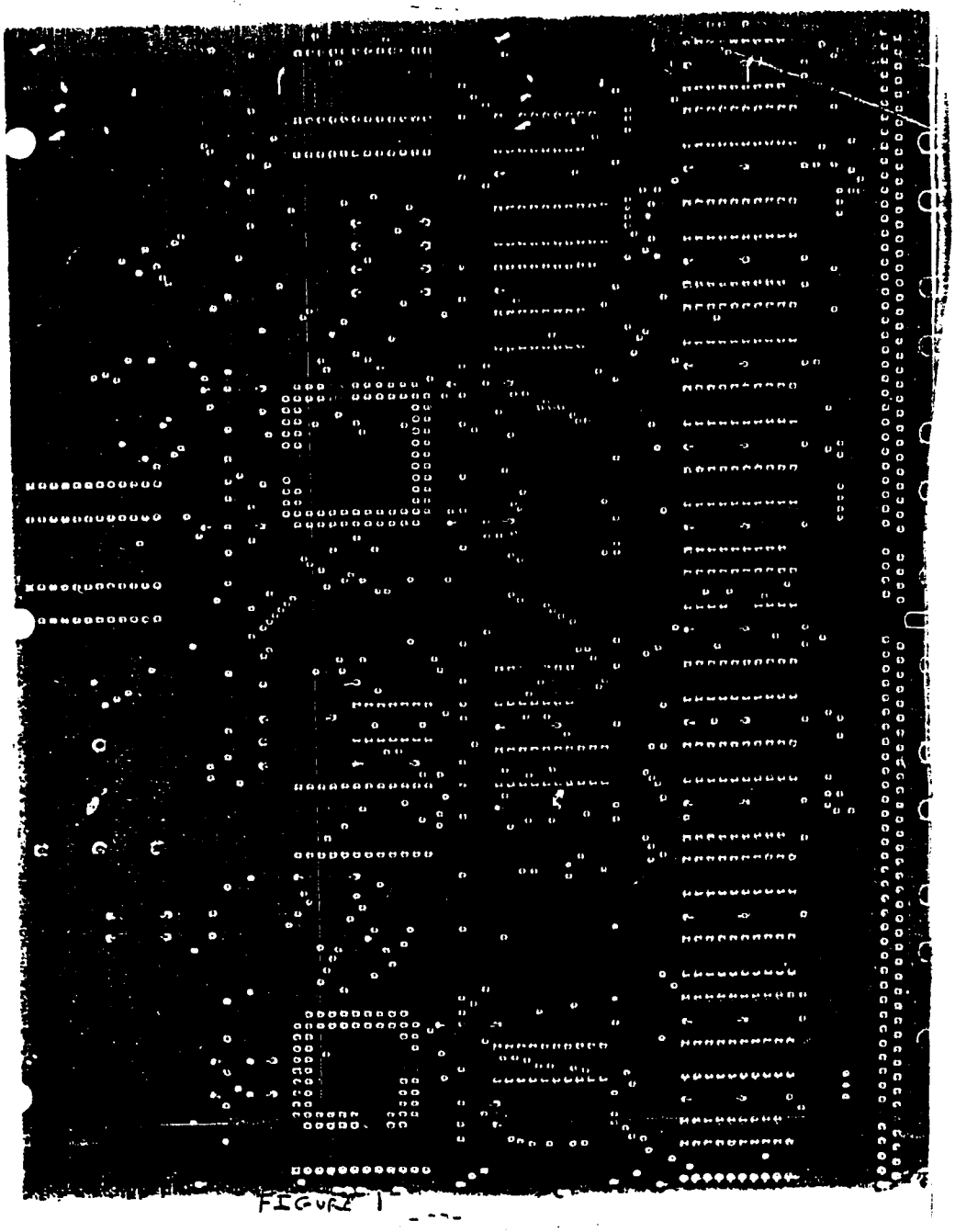

Figure 1. Experimental Circuit Board Configuration

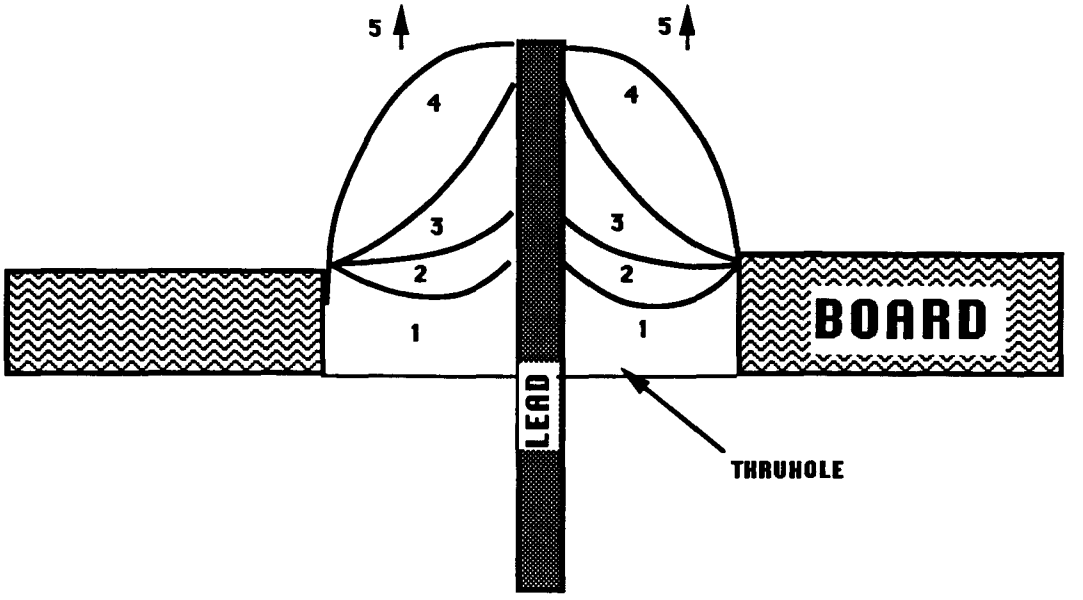

Figure 2. Thruhole Lead Solder Scoring System. Category "o" = 100, Insuff; Category "1" = 10, Min. Acc.; Category "2" = Acceptable; Category "3" = 1, target; Category "4" = 10, Max. Acceptable; Category "5" = 150, Excess

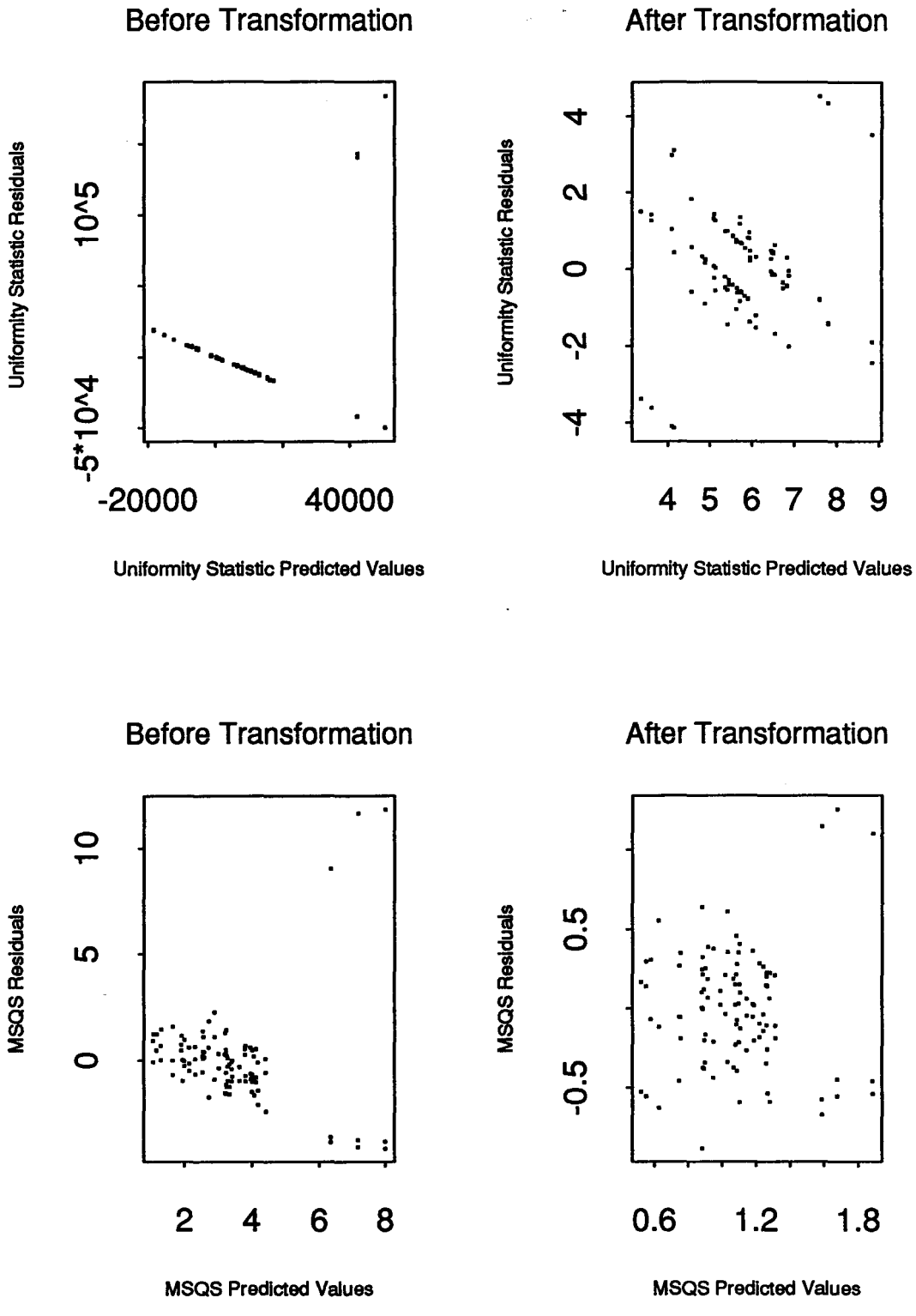

Figure 3. Residual Analysis Before and After Transformation For IC Leads