WAVE SOLDER PROCESS CONTROL MODELING USING A NEURAL NETWORK APPROACH

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ABSTRACT:
We discuss the formulation and results of a simple backpropagation approach to the control of wave soldering of printed circuit cards. Small lot sizes and a large number of different circuit card designs have complicated selection of the tunable process settings at the large manufacturer we worked with. Use of a neural network predictive model results in improved precision relative to the currently used multivariate linear model.

INTRODUCTION

The wave solder process involves (1) preheating, (2) fluxing, (3) soldering using a wave of solder, (4) cleaning, and (5) quality control. The process must be adapted according to the design (mass, size, component density, component type, etc.) of the circuit card to optimize quality, i.e. minimize solder connection defects. Process parameters which are controllable are the preheat temperatures and the line speed. Circuit card manufacturers produce products of great diversity in small lot sizes, compounding the selection of good process settings. Manufacturers have relied on establishing process settings by trial and error or simplified analytic models.

MODEL FORMULATION AND PRELIMINARY EXPERIMENTS

Some manufacturers rely on linear models to select process settings based on predicted average surface temperature of the circuit card (Brinkley 1993, Scheuhing and Cascini 1990). These models can work well, but are limited by their assumption of functional form. We began our study by investigating the appropriateness of a non-linear modeling technique. The manufacturer we worked with had 204 historic experimental observations which they had used to construct a linear model for process setting selection. Four preheat temperatures (1-4), line speed (5), circuit card mass (6), component mass (7), card thickness (8), solder pot temperature (9), ambient temperature (10), temperature of the card after fluxing (11), temperature of the card after each preheater bank (12-15), and emissivity of

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the card (16) were used as independent variables, while the dependent variable was mean card surface temperature upon entering the wave. We randomly selected 75% of the data to build a linear regression model, a second order polynomial regression model, and a backpropagation neural network. The polynomial model was constructed by considering first and second order terms for each independent variable and all first order interactions. All significant independent variable terms at $\alpha = 0.05$ were included. The backpropagation network consisted of 16 input neurons, 10 hidden neurons in one layer, and one output neuron. The network was trained using a backpropagation algorithm modified to perform a quasi-Newton minimization of squared error with an explicitly calculated Hessian matrix (El-Jaroudi and Makhoul 1990, Leuenberger 1984). The adjusted coefficient of determinations (r^2) for the linear and polynomial regressions were 0.86 and 0.93, respectively. The comparative root mean square error (RMSE) results are shown for both the training set (75%) and the test set (25%). The improvement by adding non-linearities to the model (the polynomial regression and the neural network) encouraged the project team to believe that a neural approach would indeed yield improvement over a strictly linear model.

Table 1: Error in °C for Historic Data on Mean Temperature.

Method	Training Set RMSE	Test Set RMSE
Linear Regression	6.705	7.071
Polynomial Regression	4.790	4.744
Neural Network	1.825	2.65

Concentrating on the neural network approach, we found one previously reported similar effort. Maleve et al. (1992) also applied a neural network approach to wave soldering by using circuit card design characteristics as input variables and preheat temperatures and line speed as the output variables. This assumes that the current process settings are optimal. They were unable to achieve successful results. We took a similar approach to Maleve et al. with the fundamental difference of partitioning the process into stages. The first stage is the preheating and fluxing of the circuit card up to the point of entry to the solder wave. The second stage uses the inputs of the first stage model along with the card thermal condition upon entering the wave, as predicted by the first stage model, to predict the solder quality. This allows an intervening point - thermal condition at the wave. The technical personnel at the plant believed that thermal profile of the card as it enters the wave is the single most important determinant of soldering quality. Thermal condition at the wave is only observable through special experimentation, as is described below. It is not feasible to measure thermal characteristics of each card during production.

The manufacturer had about 700 observations of production data spanning several years showing the length, width, thickness, unloaded mass, loaded mass and the number of solder connections of each circuit card, the settings of the four preheaters, the line speed and the number of solder defects. Although each preheater can be operated independently, the four preheaters were treated as two banks of two, that is, each pair of preheaters were set at the same temperature. Missing from the production data was the effect of alterations in preheat temperature and line speed, and the resulting thermal condition of the card at the wave.

To supplement the production data, we designed an experiment using two typical circuit cards. These experiments provided data concerning the main and interaction effects of the process settings on the thermal condition at the wave. We altered the line speed and four preheater temperatures individually over five levels in a fractional factorial design of 56 experiments. We attached ten temprobe temperature sensors on top of the card, and fed these into two MOLE (Multichannel Occurrent Logger Evaluator) data recording devices. This setup allowed sampling at 1 Herz of 10 temperatures at distinct locations on the card. We selected the probe locations to provide maximum information about the thermal condition of the card. Probe locations were selected to characterize both average temperature and temperature extremes, such as those encountered near a heat sink, or near a particularly large component. Because these experiments were to be run only once, we first tested the repeatability of the process. Small changes from run to run were observed, but the variation of properly crafted experiments was small. Figure 1 shows a typical repeatability plot for 6 runs of one temprobe.

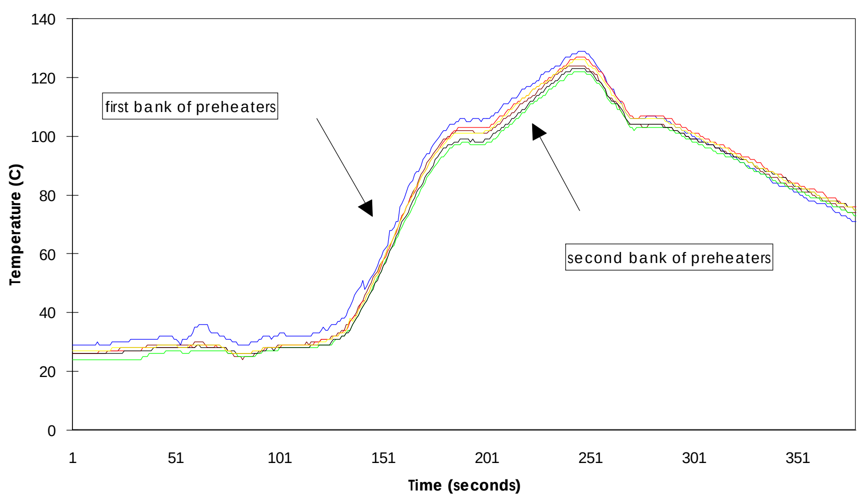

Figure 1: Repeatability Plot of Card Surface Temperature at One Location.

THE FIRST STAGE MODEL

The designed experimentation resulted in 56 observations (2 circuit cards times 28 experimental levels). We used these to train five neural network models with different target outputs. The inputs to each neural network model were narrowed down from the 16 described above to 9 variables, which the wave solder technical personnel believed best determined the thermal profile at the wave. These are the four preheat temperatures, the line speed, the number of power and ground planes, the loaded and unloaded card mass, and the card thickness. One of the circuit card design features - number of power and ground planes - could not be initially considered in the model because all of designed experiments were performed on cards with a uniform number of these planes (four), because of the availability of the cards for testing. The output of each of the five networks was a single analog neuron describing mean card temperature, range of card temperature, standard deviation of card temperature, mean temperature gradient and maximum temperature gradient, respectively. Temperature gradient was calculated using a least squares regression line over a moving window of 5 seconds from the last bank of preheaters to the wave. These five outputs were selected to provide a summary of the thermal profile of the card as it enters the solder wave. Each network consisted of 9 input nodes, one hidden layers of 6 neurons and 1 output node.

While we used all 56 observations to train the networks that provided the initial foundation of the second stage model discussed below, we validated the first stage model by the bootstrap resampling method (Efron 1982, Gong 1986, Twomey and Smith 1993). This allowed us to perform a thorough validation while using all the data to construct the ultimate neural network model. Because our data was sparse, we had to maximize the use of each data point. Standard cross validation of neural networks, as was performed above for Table 1, uses only a subset of the data for training, and the rest of it for testing. The final model does not reflect all the data. The bootstrap method, although it is computationally intensive, allows use of all data for both training the final model, and testing each bootstrap model.

The bootstrap method was performed by uniformly randomly selecting a training set of 56 observations. This was done **with replacement** 100 times. The 100 networks with identical architectures, learning parameters, weight initializations, and termination criteria were trained. Each was tested on the observations not selected for that bootstrapped sample. Table 2 shows the test set and training set error over the 100 bootstraps for each of the five networks, and the corresponding entire data set error. Note that the entire data set error is a combination of training points and testing points which varies with each bootstrapped network. As might be expected, prediction of mean temperature is easier than prediction of temperature extremes or variation. Similarly prediction of mean temperature gradient is easier than prediction of maximum temperature gradient. Figure 2 shows the plot of mean absolute error over the 100 networks for the mean temperature prediction. The variation among these networks is due entirely to the selection of the training and testing samples.

Table 2: Error in °C Over 100 Bootstrapped Networks.

Output	Mean Value	Training Set		Test Set		Entire Data Set	
		RMSE	MAE	RMSE	MAE	RMSE	MAE
Mean Temperature	100.41	3.29	2.50	7.82	5.53	4.96	3.61
Temperature Range	34.375	3.56	2.78	8.29	6.14	5.30	4.02
Temperature Std. Dev.	11.19	1.07	0.83	2.68	1.97	1.67	1.25
Mean Temp. Gradient*	-1.38	0.13	0.09	0.30	0.21	0.19	0.14
Max. Temp. Gradient*	-2.586	0.33	0.24	0.80	0.56	0.50	0.36

* In °C per second.

To compare the bootstrapped results with a more conventional method of neural network validation, we performed a three fold grouped cross validation using the same data and the same neural network architecture. The cross validation was done for the target outputs of mean card temperature, temperature range, temperature standard deviation and maximum temperature gradient. Table 3 gives the training and testing error for the average of each three fold cross validation. Results are fairly consistent with those found in the bootstrap validation method, except these networks exhibit some over-training which did not occur for the bootstrapped networks (when training was terminated earlier).

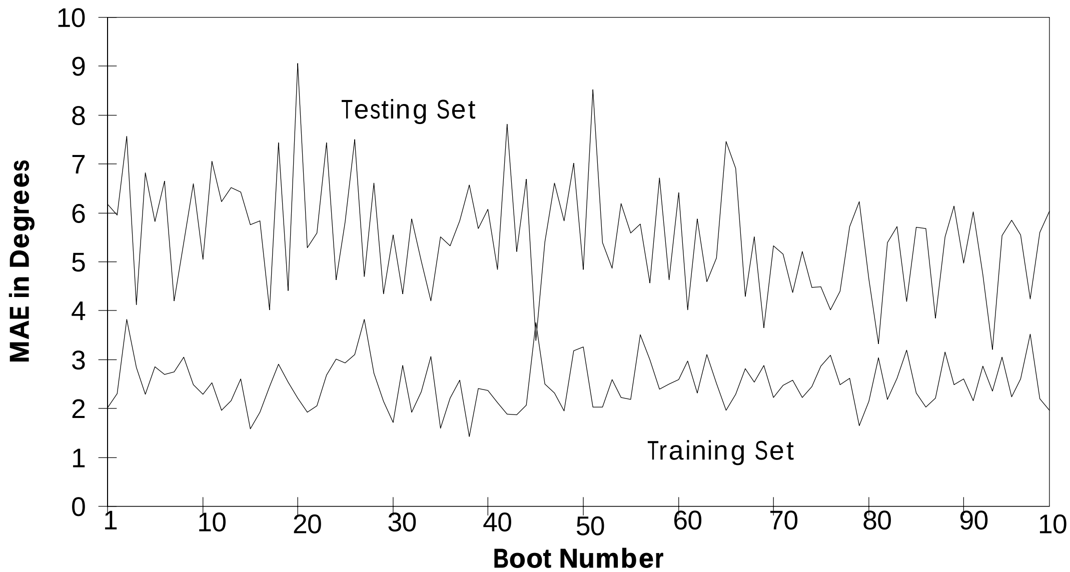

Figure 2: MAE for Training and Testing of Mean Temperature Bootstrapped Networks.

Table 3: Error in °C for Three Fold Cross Validation

Output	Mean Value	Training Set RMSE	Training Set MAE	Test Set RMSE	Test Set MAE
Mean Temperature	100.41	1.60	1.01	10.45	8.95
Temperature Range	34.375	2.62	1.94	14.56	12.16
Temperature Std. Dev.	11.19	0.70	0.51	3.29	2.50
Max. Temp. Gradient*	-2.586	0.22	0.18	1.02	0.73

* In °C per second.

Because the data was from a designed experiment, and not randomly selected, this test set performance is a worst case, with average performance likely to be better. We were satisfied with the performance of the bootstrapped and cross validated networks, but were concerned about the very limited sample (two) of card designs. To supplement the designed experiments, we have begun gathering of thermal profiles on production cards. This data will have complete thermal information, design information and quality information. The quality information was not available from the designed experiments since we could not solder the cards. We are adding two design variables as inputs - the number of power and grounds planes, and whether a heat sink is present on the card. We anticipate that about 50 different card designs with complete data will be gathered over a month of production runs. This effort is currently underway.

THE SECOND STAGE MODEL AND CONCLUSIONS

We are still in the process of taking production data to build a robust Stage 1 model, so the Stage 2 model is future work. This model will be designed to take the inputs of thermal condition at the wave, generated from the Stage 1 neural network discussed above, along with the circuit card design information and the process settings to predict quality of solder connections.

This case study shows the application of neural network modeling to a complex process in a live manufacturing environment by working around several major constraints. The first constraint was the inability to monitor the soldering process as the card goes through the wave. We used thermal condition just prior to entering the wave as a surrogate to estimate success of soldering. The second constraint was the lack of complete data. The designed experiments provided a full thermal data set on a minimal number of card designs, but no soldering quality data. The historic data used in the linear model described in the first section had more card designs, but limited thermal data (mean card temperature only) and no quality data. Available production data covered a wide spectrum of card designs and complete quality information, but alterations in process settings for a given card design were few and there was no thermal information at all. We worked around this data constraint by breaking our system into two stages so that we could build and verify the neural network models individually.

Once the Stage 1 and Stage 2 neural networks are determined to be satisfactory over the range of production cards, the models could be inverted to select process settings (preheat temperatures and line speed) to optimize for solder connection quality. This inversion could also be extended to circuit card design variables, to optimize for manufacturability for future card designs.

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