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NEURAL NETWORK OPEN LOOP CONTROL SYSTEM FOR WAVE SOLDERING

DAVID W. COIT*
Department of Industrial Engineering, Rutgers University,
96 Frelinghuysen Rd., Piscataway, NJ 08854, USA
coit@rci.rutgers.edu

BONNIE TURNER JACKSON and ALICE E. SMITH†
Department of Industrial and Systems Engineering, Auburn University,
207 Dunstan Hall, Auburn, AL 36849, USA
† *aesmith@eng.auburn.edu*

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This paper describes the development of neural networks for the prediction of (1) printed circuit card surface temperature during a wave soldering process, and (2) the quality level of the circuit card assembly soldered connections. Using a combination of production data and design of experiment data, a set of hierarchically connected neural networks were developed and validated. These networks predict thermal behavior of a printed circuit card assembly at various points in the solder process based on process settings and circuit card design data. Then these predictions are used as inputs, together with other parameters, to estimate the quality of solder connections. The system can be used to decrease the number of solder connection defects, reduce set-up and preparation time between lots, and lead to consistent, repeatable process settings without trial production runs or operator tuning efforts. For the wave soldering process studied, this is especially important since the batch size is quite small, quality demands are stringent, and process settings are changed frequently.

1. Introduction

The wave solder process involves (1) preheating, (2) fluxing, (3) soldering using a wave of solder, (4) cleaning, and (5) quality control as shown in Fig. 1.[1] Circuit cards are passed through the wave flux, two banks of pre-heaters, and then, wave solder is applied. The cards are trimmed, and then cleaned. The parameters which influence the wave solder process are[2,3]:

In-Process Variables

1. Temperature of the circuit card upon entering the wave solder system (the ambient temperature).
2. Temperature of the circuit card after the wave flux.
3. Temperature of the circuit card after the first bank of preheaters (there are two banks with top and bottom sections in each).
4. Temperature of the circuit card as it exits the second bank of preheaters.
5. Temperature of the circuit card immediately prior to entering the solder wave.

Process Settings/Parameters (Directly Controllable Variables)

6. Four preheat section temperatures (first and second, top and bottom).
7. Conveyor speed and carrier spacing at which the circuit card passes through the wave solder system.
8. Solder pot temperature.
9. Type of flux.

*Corresponding author.

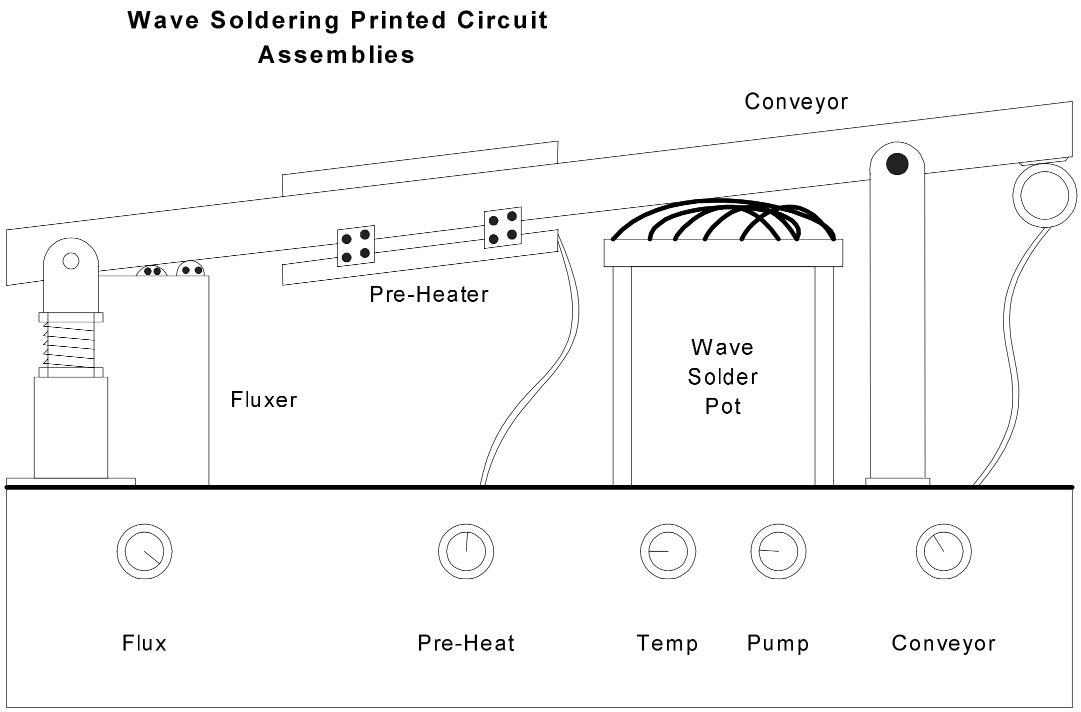

Fig. 1. Wave solder process.

Circuit Card Design Variables

10. Mass of the bare circuit card.
11. Mass of the components on the circuit card.
12. Thickness of the circuit card.
13. Emissivity (infrared absorptivity) of the circuit card.
14. Printed circuit card material.
15. Presence of surface ground planes which acts as infrared reflectors.

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 preheater temperatures in two banks and the line speed. Because of operational considerations, the manufacturer choose to set both banks of preheaters to a single temperature thus condensing this to a single variable. The manufacturer produces products of great diversity in small lot sizes, compounding the selection of good process settings. Compensation for these product-specific characteristics could be accomplished only through periodic manual measurements and adjustments. Manual operator intervention, although better than none, requires continual effort and diligence to maintain optimal conditions because of the diversity of circuit card designs.

This project focused on the development of a new approach for predictive process control based on neural networks. Modern controllers can monitor and compensate for equipment performance automatically. However the relationship of the circuit card design, equipment settings and observable process parameters to an optimal quality level has yet to be defined. Thus, modern controllers can automatically maintain a pre-established temperature, but they cannot automatically adjust to achieve quality goals.

One method, that some manufacturers have relied on to establish process settings, is operator trial-and-error to respond to quality deficiencies, process constraints or new products. This is inefficient since it necessarily involves wasted time and products, and it is often ad hoc, where results depend on the skill and judgment of the particular operator. It is also generally not repeatable and there is no basis for pro-active control. The second method commonly used for selection of wave solder process settings is a linear regression model.[4,5] Such models do provide a vehicle for pro-active control and repeatable response. However, the process may or may not adhere to the assumptions of functional (usually linear) or parametric (usually Gaussian) form. Thus, the model may have inherent errors due to incorrect assumptions which cannot be compensated. These models usually have poor robustness in light of new constraints and products, or noise in the data.

The principal research objective was to develop a non-linear, multivariate, predictive control system for the wave solder process so that process settings (line speed and preheat temperatures) which facilitate good quality solder connections can be selected *a priori* for each circuit card design. It was determined that the thermal profile of the circuit card (surface temperature, rate of temperature dissipation and thermal uniformity) as it enters the solder wave is the best determinant of solder connection quality. The software predictive control system has been designed in two connecting models. The first part is a descriptive model of the thermal condition of the card at the wave based on inputs of the circuit card design specifications (mass, component density, size, etc.) and the process settings. The second model is a descriptive model of the ensuing solder connection quality (a categorical measurement of excellent, good and fair quality) based on the input from the first model.

Neural networks have already been successfully applied for electronics assembly to model various aspects of the process, most often to assess the quality of individual solder connections. However, the use of neural networks, to predict printed circuit card surface temperature and quality levels for the assembly, is unique. There has been prior research to assess the quality of a finished solder connection based on a digitized image.[6–10] Although each solder connection can be somewhat unique, in these applications neural networks have been successfully used to distinguish good versus defective connections. This has resulted in meaningful reductions in circuit card assembly inspection time. Other uses of neural networks to assist in electronics assembly has been to anticipate failures for automated component placement,[11] and to model pool-boiling for vapor phase soldering.[12]

2. Modeling Approach

It is generally believed that there is an optimal thermal profile which will lead to good solder connection quality. For example, military specifications require a preheat temperature of 200°F plus 20° or minus 40°. The thermal profile is accomplished with a combination of maintaining proper solder temperatures through heating of the reservoir, and through preheating the card to a suitable temperature prior to the wave so that thermal shock does not occur in the wave. Maintaining the solder reservoir temperature is relatively easy to do; the problem lies in heating the card so that it acquires the optimum soldering temperature, distributed uniformly throughout the card as it is being soldered, in spite of widely varying geometries, thicknesses, component layouts and the presence of heatsinks, that often diminish the benefits of pre-heating.

Using thermal condition at the wave as an intermediate point for the final estimation of solder connection quality necessitated a hierarchical approach to modeling. Predictive models were necessary because the method of measuring card thermal condition during wave soldering is too intricate and time consuming to be done regularly during production. To obtain the most accurate predictions of thermal condition at the wave, two intermediate thermal models are used. The first predicts mean surface temperature at the first bank of preheaters and the second predicts mean surface temperature at the second bank of preheaters. The model at the second bank of preheaters uses the prediction of the mean temperature from the first bank of preheaters and the models at the solder wave use the prediction of the mean surface temperature at the second bank of preheaters. The final stage model uses the card design inputs of the first stage model along with the card thermal condition upon entering the wave, as predicted by the first stage model, to categorically predict the solder connection quality.

Neural networks were used for the predictive control system because of their proven performance in non-linear process control and their abilities to learn complex, multivariate, non-parametric, dynamic and noisy relationships (see for example, Refs. 13 and 14). Relationships do not assume a pre-defined probability distribution nor do they need to be defined with an empirically or theoretically developed algorithm. Neural networks learn relationships from the data itself, tuning their internal parameters so that relationships are not only suited to the sampled data, but can be generalized to new and different data.[15] Many neural networks, including the kind used in this work, have the property of being theoretic universal approximators[16–18] unlike their statistical counterparts.

In process modeling and control, neural networks frequently aid or support the decisions a machine operator is required to make. Cariapa, Akbay and Rudraraju[19] explored the use of neural networks to automate tool polishing for optimal results. A similar study[20] focuses on modeling creep feed grinding of superalloys to achieve the desired surface finish. These processes are similar in complexity to wave soldering. The research approach in both cases provides a basis for the approach adopted in this paper. In the past, models of wave soldering incorporated linear techniques which ignore or minimize the nonlinear properties of wave soldering.[4,5] Malave and Sastri[21] explored the use of neural networks to relate process parameters (preheat temperatures and line speed) with board characteristics (e.g. size, weight, etc.). They attempted training three networks, each with different inputs, but were unsuccessful. Their lack of success was attributed to poor selection of design parameters (inputs) and lack of data. An early preliminary study by the authors[22] indicated promising results with neural networks when used to predict solder connection quality.

It was anticipated that the relationship between card characteristics, process settings and thermal condition (and ultimately solder quality) would be nonlinear and contain interactions, neither of a specified analytic form. Because of their empirical nature, neural network predictive models are highly dependent on the data used to build and validate them.[23,24]

3. Data Gathering and Processing

3.1. *Specialized experiments*

Thermal condition at the wave is only observable and measurable through special experimentation. A set of experiments were designed using two surplus circuit cards to characterize the response of the thermal profile at the wave to changes in the process settings (line speed and preheater temperatures). These experiments provided data concerning the main and interaction effects of the process settings on the thermal condition at the wave over a range of process settings greater than normally used in production. The line speed and four preheater temperatures were altered individually over five levels in a fractional factorial design of 56 experiments.[25] Ten specialized temperature probes were attached to the surface of each circuit card, then connected to two data recording devices. This setup allowed sampling at 1 Hertz of 10 temperatures at distinct locations on 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 (with large thermal mass).

The data had to be processed extensively before it could be used for model building or analyzed statistically. First, the multiple probe readings (up to ten per card) had to be aligned in physical location on the line. The data recording devices started reading all probes at the same time. However, each probe was transported down the line at a different offset from the front of the card. This offset had to be eliminated so the thermal profiles reflected the readings at the same physical point on the line when solder was applied for each sample (at 1 Hertz). Using

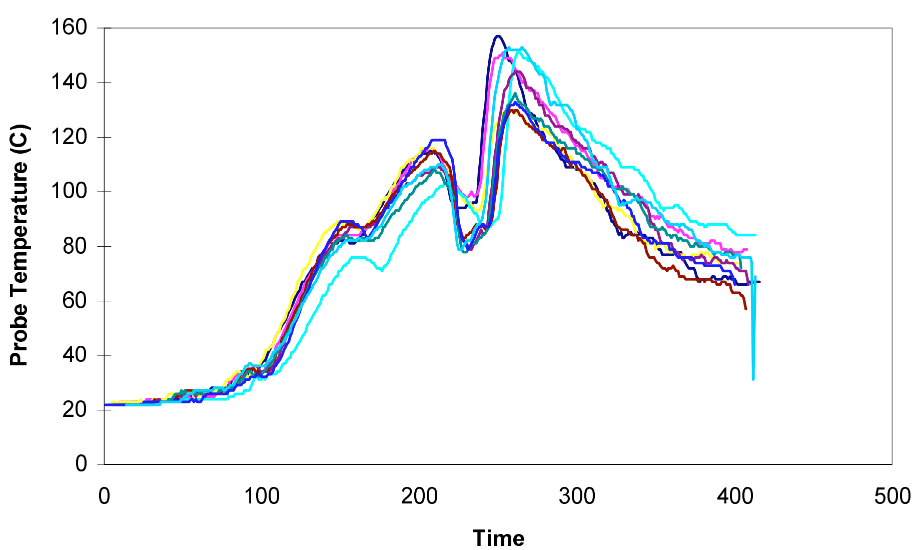

Fig. 2. Typical set of probe readings from a wave solder experiment.

the circuit card drawings showing the precise probe locations, the offset of each probe from the beginning of the card was measured. The line speed was then used to calculate the exact offset, in seconds, and align the data for each probe. A typical output from such an experiment is shown in Fig. 2.

Summary statistics of the thermal profile at the wave were computed: mean temperature, temperature range, standard deviation of temperature, mean temperature gradient and maximum temperature gradient. The mean temperature gradient was the maximum slope of the least squares regression line (where x = time and y = temperature) over a moving window of five observations. This variable was a simplified surrogate for the rate of heat dissipation as the card entered the wave. The maximum temperature gradient was the single steepest slope over all probes.

3.2. *Production data*

Because the specialized experiments were limited to two circuit card designs (the only surplus available), the number of different circuit card designs considered needed to be expanded. It was jointly decided by the manufacturer and the academic team that the most feasible and expedient way for this data to be gathered was for wave soldering personnel to unobtrusively collect temperature profile data on two to four cards per day during non-peak work loads. Probe locations were individually chosen for each production card (one per lot). Complete quality data included type, number and location of each solder connection defect was recorded for each card. Data was preprocessed as described in Sec. 3.1.

4. Model Building

4.1. *Statistical analysis*

There were 43 usable data sets collected during production. By combining these with the experimental data (57 sets — one of the 56 experiments had two runs), a total data set of 100 observations was available. Before commencing with the building of neural network models, a complete statistical analysis of the data was performed. Table 1 contains a description of the production data results. It can be seen that a fair amount of cooling takes place after the card leaves preheater bank 2 before it enters the solder wave. Far from uniform card temperatures are present at the wave, even though consistent and uniform heating was a primary control objective to minimize defects. The values of the range of card surface temperatures at the wave were from 11°C to 50°C. There is also quite a bit of variability among cards. Note that the temperature gradient is in units of degrees per second.

Table 2 presents a summary of statistical correlations for output variables whose absolute value is greater than 0.50, other than the preheater

Table 1. Statistics of production data.

Variable	Mean	Maximum	Minimum
Temperature at wave	95.189	127.56	68.540
Temperature range at wave	30.770	57.40	11.60
Temperature gradient at wave	−1.6620	−3.800	−0.500
Temperature at preheat 1	89.923	143.82	49.660
Temperature at preheat 2	114.57	154.62	77.180

Table 2. Significant correlation coefficients.

Variable 1	Variable 2	Type Correlation	Correlation Coefficient
Mean temp. wave	Preheater temps.	Spearman, Pearson	0.6434, 0.6622
Mean temp. wave	Mean temp. preheat 1	Pearson	0.6099
Mean temp. wave	Mean temp. preheat 2	Spearman, Pearson	0.6731, 0.7353
Mean temp. preheat 1	Mean temp. preheat 2	Spearman, Pearson	0.8690, 0.906
Mean temp. preheat 2	Preheater temps.	Spearman, Pearson	0.5887, 0.5856
Range temps. preheat 1	Range temps. preheat 2	Spearman, Pearson	0.7779, 0.7814

temperatures which were nearly perfectly correlated with each other. There were obvious correlations such as card length and width to card bare and assembled mass. More interesting results showed relatively weak correlation between preheater temperatures and card temperature at the first bank of preheaters, while the mean temperature at the wave was strongly correlated to both preheater temperatures and card temperatures at each bank of preheaters. As expected, both sets of temperature means and ranges at each bank of preheaters were strongly correlated. The analysis indicates a lack of correlation between gradient of the temperatures at the wave and range of temperatures at the wave with any other variables. This indicates that a purely linear model will be inadequate for predicting these values.

4.2. *Regression analysis*

Mean temperature at the wave was regressed in two ways. The first included only design and process setting parameters while the second included with the same variables and also the temperature conditions (mean and range) from both preheaters 1 and 2. The first achieved an r^2 (adjusted) of 0.5151 with preheater temperature, line speed and number of card layers in the regression model, while the second achieved an r^2 of 0.6034 with preheater temperature and mean temperature at preheater 2 in the model.

A similar approach for temperature gradient at the wave was pursued. The first achieved an r^2 of 0.3046 with bare card mass and presence of a heat sink included in the model. The second achieved an r^2 of 0.3845 with bare card mass, presence of a heat sink and mean temperature at preheater 2 in the model. Again, the same approach was used to predict range of temperatures at the wave. The first achieved an r^2 of 0.0 with no variables in the model. The second achieved an r^2 of 0.1774 with the range of temperatures at preheater 2 in the model.

Then a regression of mean temperature at preheater 1 was developed with an r^2 of 0.6110 with preheater temperature, card thickness, presence of a heat sink and line speed in the model. A similar regression of mean temperature at preheater 2 (also allowing thermal condition at preheater 1 as potential input variables) achieved an r^2 of 0.8797 with preheater temperature, line speed and the mean temperature at preheater 1 in the model.

In summary, a purely linear regression approach would not yield models which would explain most of the variability in the data with the exception of the mean temperature at preheater 2. In particular, the gradient and range at the wave did not adhere to a linear model. These results serve as further justification that a more advanced modeling approach, such as neural networks, is required to properly predict and characterize temperature conditions during soldering.

4.3. *Neural network models*

Six neural networks were constructed to predict the quantities below:

1. average card temperature at the first bank of preheaters (ATEMP1);
2. average card temperature at the second bank of preheaters (ATEMP2);
3. average card temperature at the solder wave (ATEMPW);
4. standard deviation of card temperature at the solder wave (STDW);
5. average temperature gradient at the solder wave (GRAD); and
6. solder connection quality (QUALITY).

Thirteen "standard" inputs for all neural network models were the four preheater temperatures, the line speed, the card thickness, the card length, the card width, the unassembled (bare) mass of the card, the assembled mass of the card, the number of layers in the card, the number of ground planes in the card, and whether a heat sink is present on the card (1 if present, 0 if not). An ordinary backpropagation algorithm was used[26] with a number of preliminary experiments to determine the number of neurons in the hidden layer. Figure 3 shows a typical neural network.

A grouped cross validation was used where a group of observations (g) is withheld for testing for each network constructed.[27] That network is trained on the remaining observations ($n - g$), then tested on the withheld observations. This is repeated n/g times (resulting in n/g trained networks). For each of the n/g networks, a different set of g observations is withheld and used as testing patterns. After developing each network, a final network using all n observations for training is built. The estimate of error is based on the testing observation performance of the n/g cross validated networks and the apparent error (error on the n training observations)

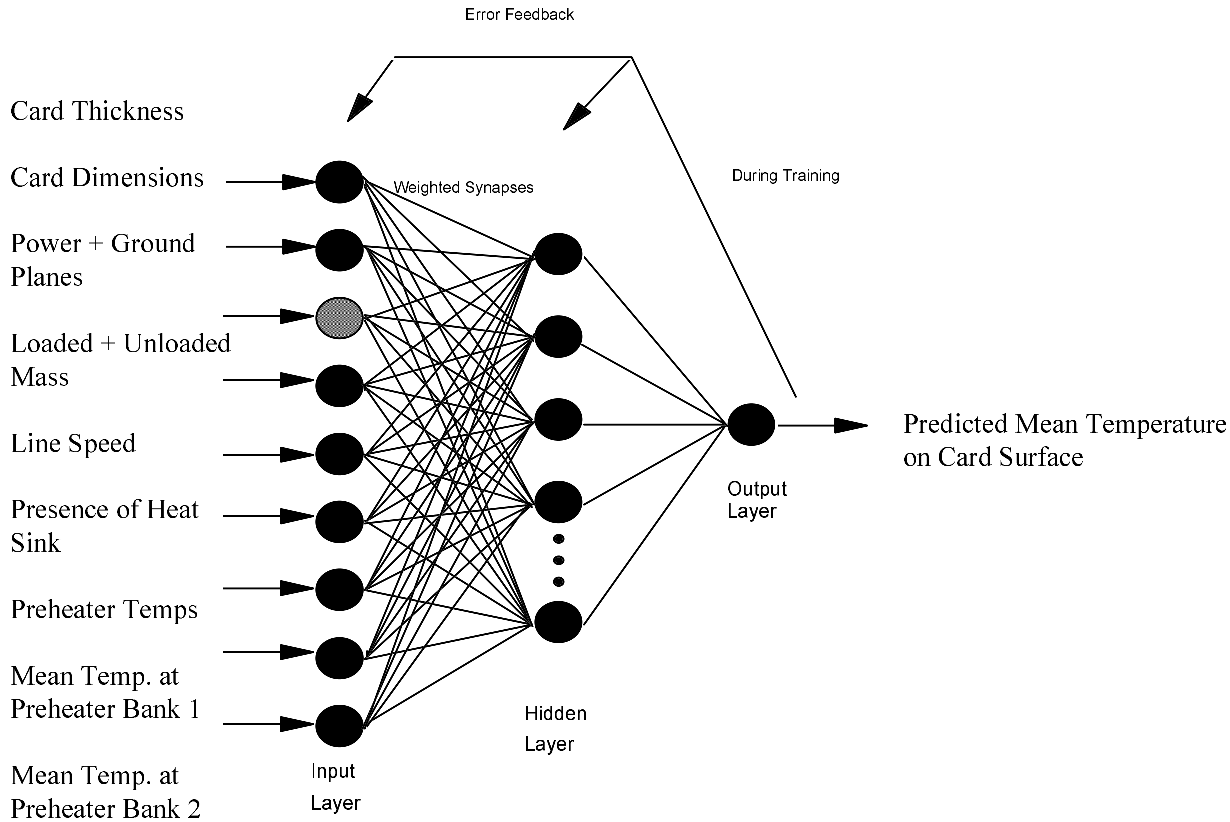

Fig. 3. Typical neural network architecture.

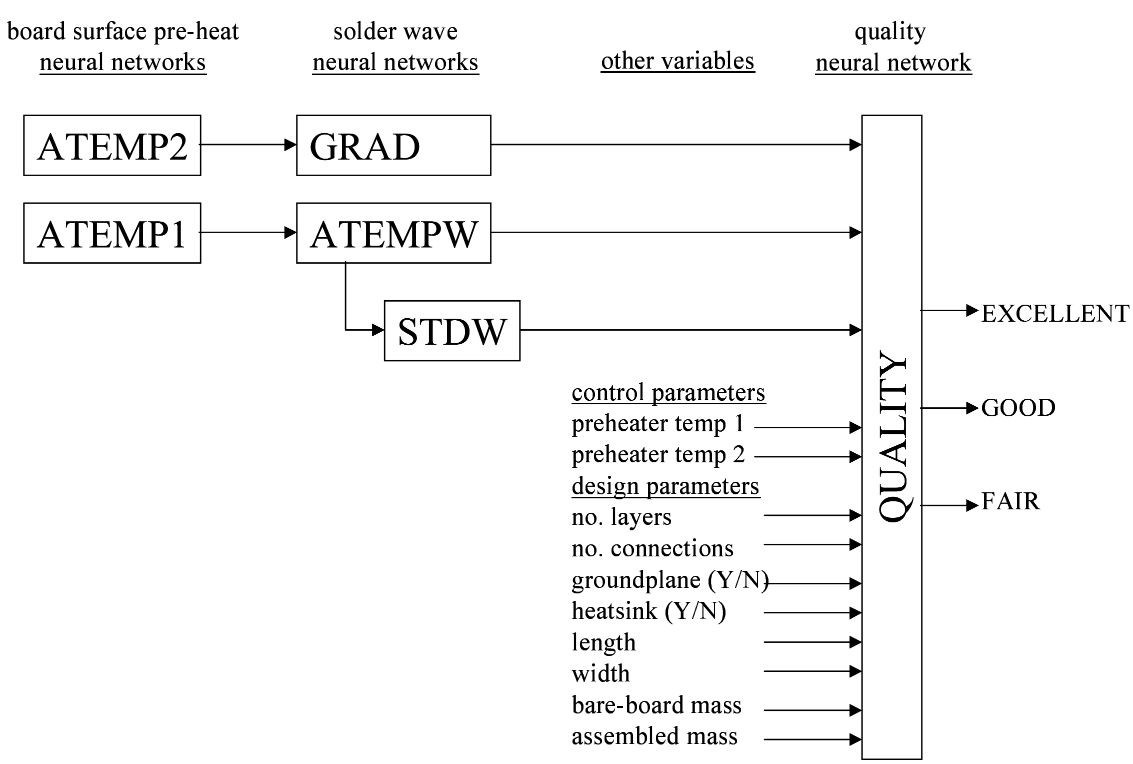

Fig. 4. Input variables for the six predictive neural networks.

of the final network. A n/g of five was selected (also called a five-fold cross-validation), so that five cross-validated networks were constructed, each trained on 80 observations and tested on 20.

The input strategies for the networks predicting thermal condition at the wave and for final quality are shown in Fig. 4. The inputs to the networks predicting the mean temperature at each bank of preheaters (ATEMP1 and ATEMP2) are the 13 standard inputs. Each subsequent network (ATEMPW — mean temperature at the wave, GRAD — gradient at the wave, STDW — standard deviation at the wave) also contained the thirteen standard inputs along with outputs from earlier neural networks in the hierarchy.

5. Results

Table 3 shows the mean absolute error (MAE) over the training set (used to construct the model) and the test set (new data to the model) in absolute units and as a percentage. Remember that these results are from five cross-validated networks and a final whole data set network, as described in Sec. 4.3. MAE is computed by averaging the absolute value of the error, i.e. |predicted–observed|, over the data set (training or test). In Table 3, %MAE conveys the same data except the absolute value of error is presented as a percentage of the observed value.

In general, error somewhere closer to the training set than the test set would be expected from the population as a whole (i.e. that which would be encountered during on-line operation). The training set error is more indicative of the expected error since overfitting was controlled and the network was built using all 100 observations, rather than four-fifths of the data, as were the testing networks. The networks predicting mean temperatures (at the preheaters and at the wave) were quite precise with errors well under 10%. The networks predicting standard deviation and gradient were significantly less precise with errors between 15% and 30%. It is much more difficult to predict variable data than that which has been smoothed by averaging. Although the errors on the testing sets were larger than that of the training sets, the difference is small. This indicates that the networks are not overfitted or overtrained. Overparameterization is a common problem in neural networks, especially under conditions of relatively small data sets.[24]

Though the thermal profile at the wave could be used as a surrogate for solder quality and the first stage model could be used by itself to select process settings (and this is currently how the linear regression model is used at the manufacturer), it is preferable to explicitly relate circuit card thermal profile to solder quality. To this end, number of solder connections per card, and number of solder connection defects by type and location per card were gathered on 68 of the cards (some of the specialized experiments could not record quality data).

The 13 standard inputs, less card thickness, and adding the thermal condition at the wave, as predicted by the neural networks (mean surface temperature, standard deviation of surface temperature and temperature gradient) were used as inputs to the neural network. There were two hidden layers with 15 and 3 neurons, respectively. There were three binary outputs which equated to solder quality categories of excellent (0 to 4 defective connections), good (5 to 12 defective connections) and fair (more than 12 defective connections). A categorical metric for quality was used because the small size of the data set would not support precise predictions of the number of defective solder connections.

Table 3. Mean absolute error and percent error for neural network models in °C ($n = 100$).

Predicted Variable	MAE–Training	%MAE–Training	MAE–Testing	%MAE–Testing
Mean temp–Wave[a]	5.22	5.57%	6.63	7.19%
Temp gradient–Wave[b]	0.24	17.55%	0.32	24.02%
Standard deviation–Wave[c]	1.92	20.95%	2.44	27.26%
Mean temp–Preheater 1	6.78	7.90%	8.44	9.64%
Mean temp–Preheater 2	7.05	6.20%	8.26	7.53%

[a] using mean card temperature at preheater 1 as input
[b] using mean card temperature at preheater 2 as input
[c] using mean card temperature at the wave as input

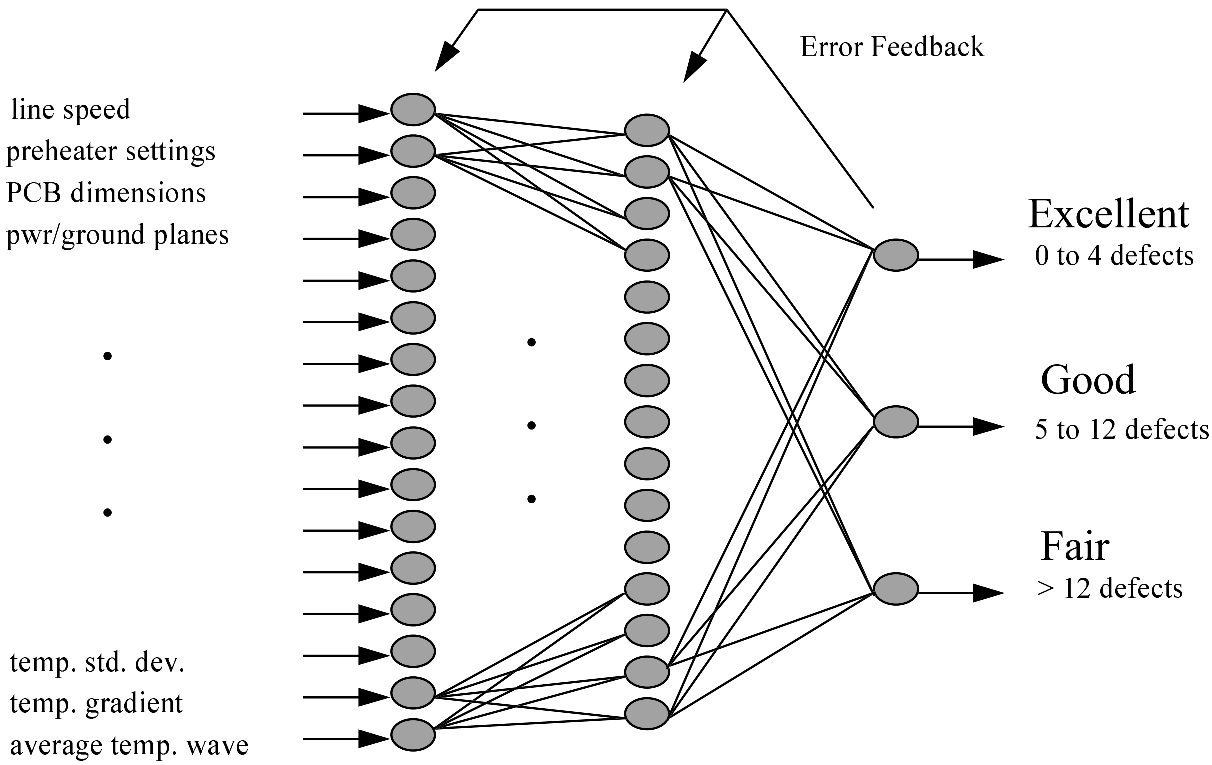

Fig. 5. Neural network architecture for quality prediction.

Table 4. Quality predictions for training and testing sets.

Data Set	No. Correct	% Correct	Error Type		
			I	II	III
Train	45	78.9	7	3	1
Test	76	82.6	9	4	3

The selected neural network architecture (two hidden layers, 15 and 3 neurons) was determined empirically. Several different architectures were considered based on the researcher's past experiences. The selected network performed best, although each attempted network considered performed accurately and yielded similar results.

The number of observations in the good and fair quality categories were increased artificially by copying selected observations because neural network training places equal probability mass on each training observation. Therefore, a category with few observations would be "overwhelmed" by the dominant category (in this case, excellent). The resulting model would tend to overpredict that dominant (excellent) category. Figure 5 shows the neural network architecture of the quality model.

Classifications were achieved by interpreting the output node (output classification) with the largest numeric output to be the chosen class. So an output with Excellent = 0.91, Good = 0.25 and Fair = 0.12 would be interpreted as the excellent category. While analyzing the data, three error types emerged.

- Type I: excellent circuit card was mistakenly identified as good.
- Type II: excellent circuit card mistakenly identified as fair.
- Type III: good card was identified as fair.

The performance of the quality network was encouraging as shown in Table 4. It would have been preferable for the network to never make an error. However, it should be noted that errors that did occur were generally small. In the majority of cases where the network was in error, the prediction was in the closest categorical defect level. Also, it was beneficial that in all cases where the network was in error, it predicted a higher defect level, rather than a lower defect level. Thus, the model was conservative. This conservative model would prevent users from choosing process settings which were mistakenly predicted to yield the best quality (excellent category).

6. Software System

The neural networks were developed in a commercial specialized neural network development software designed to run on a PC. The completed neural networks were compiled to C executable files. These files are called by the user interface module, which runs under Visual Basic for Windows. The user interface contains pull down menus, input screens and options to save results to an ASCII file. A screen is shown in Fig. 6 where the user has to input the process settings and the card design parameters, and the system has returned the predictions of card temperature profile and solder quality. The user would use the system to choose a good set of process parameters for a given circuit card design. In the case in Fig. 6, the user would want to choose different process settings to move the quality prediction into the excellent category. A further enhancement to the system would be an optimization module that would select process settings automatically. The manufacturer did not want the process settings step automated to this extent currently as technicians wished to retain control of the process and see exactly how process decisions were made.

7. Conclusions

For soldering diverse circuit card designs in low production quantities, the efficient adjustment of wave solder process settings is critical to produce high quality soldered circuit card assemblies and to minimize inefficient process fine-tuning. The relationship of circuit board geometries, wave solder process settings and product quality are complex, yet most systems are adjusted in an ad hoc fashion based on the skill and experiences of the operator. The hierarchical neural networks described in this paper offer significant advantages. Process changes to react to different batches can be made efficiently so that manufacturing can be done as a continual process. Additionally, the neural network models successfully

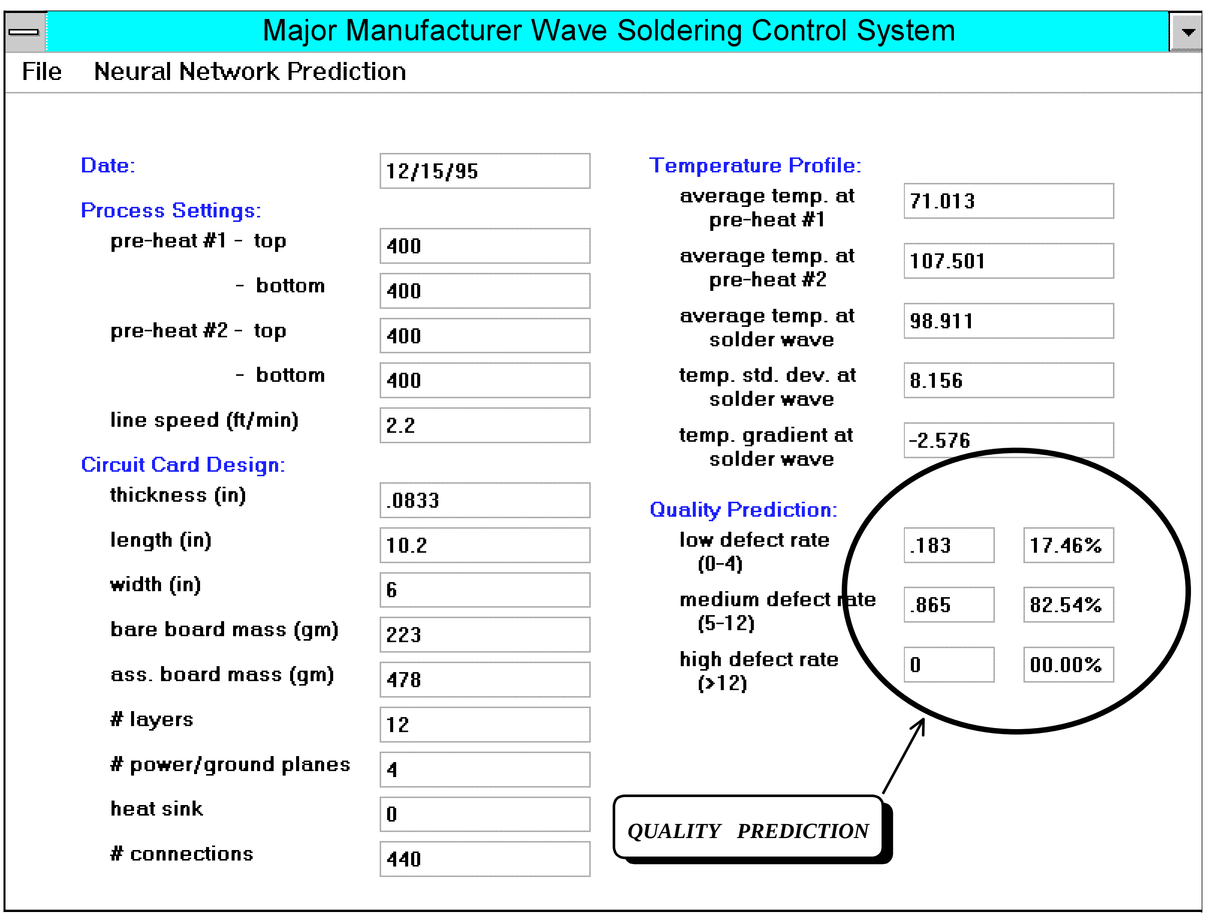

Fig. 6. Screen from open loop predictive control system.

modeled the relationship with solder defects qualitatively so the defect rates can be continually decreased as part of a continuous variability reduction manufacturing process.

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