Cite as *Proceedings of the Fourth Industrial Engineering Research Conference* (IERC) May 1995

USING DESIGNED EXPERIMENTS TO PRODUCE ROBUST NEURAL NETWORK MODELS OF MANUFACTURING PROCESSES[1]

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ABSTRACT

Neural networks are beginning to be used for modeling of complex systems, often in process and quality control of manufacturing processes. Since neural networks are wholly empirical models, the resulting model is highly dependent on the data used to construct it. Using data from production lines ensures integrity, however may produce biased samples which do not reflect the entire range of domain operation. Supplementing production observations with data gathered from designed experiments alleviates this problem of overly focused data sets. This paper describes this designed experiment supplemental approach as it was used on two research projects involving complex manufacturing processes.

INTRODUCTION

Neural networks have many attractive properties for modeling of complex systems: universal function approximation capability, resistance to noisy or missing data, accommodation of multiple non-linear variables with unknown interactions. For processes where no satisfactory analytic model exists or where a linear model is inappropriate, neural networks are a good alternative approach. Two such processes are wave soldering of circuit cards and casting of large ceramic ware products. There are many variables which affect the ultimate outcome of these processes, however they are highly non-linear and contain substantial unknown analytic relationships. To effectively control such processes without substantial trial and error tuning, a predictive model is required.

A neural network predictive model has the advantages listed above, however there are drawbacks as well. A primary concern is that neural networks act as “black boxes,” and moreover, are empirical “black boxes.” This means to operate a neural network model effectively and to assure operator confidence in the model, the model must be constructed of data which adequately reflects the process domain. This domain will often include variable values not commonly seen during production (extreme values), but for which it is necessary that the neural model properly handle. Therefore, the data gathered to construct the model should include production ranges along with designed ranges. Two such situations arose in the course of the authors’ funded research with manufacturing organizations. These are the wave soldering of circuit cards and ceramic casting of large sanitary ware. For more details concerning these processes see (Coit et al. 1994, Martinez et al. 1994).

THE WAVE SOLDER PROCESS

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

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[1] Part of this work was supported by the Ben Franklin Technology Center of Western Pennsylvannia and by Lockheed Martin Corporation.
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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.

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. Concentrating on the neural network approach, there is one previously reported similar effort. Maleve et al. (1992) 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.

The approach taken in this paper was to model what the technical personnel at the plant believed was the single most important determinant of soldering quality - thermal profile of the card as it enters the wave. 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. To measure thermal profile, ten temperature sensors were attached on top of the card, and fed into two MOLE (Multichannel Occurrent Logger Evaluator) data recording devices. This setup allowed sampling at 1 Herz of 8 to 10 temperatures at distinct locations on the card. Figure 1 presents a typical profile of the wave soldering process. The probe locations were selected 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.

Using the experimental setup just described, the manufacturer gathered 40 observations of thermal profile production data spanning two months 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, an experiment was designed 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. The line speed and four preheater temperatures were altered individually over five levels in a fractional factorial design of 56 experiments. Because these experiments were to be run only once, the repeatability of the process was first tested. Small changes from run to run were observed, but the variation of the properly crafted experiments was small.

THE CERAMIC CASTING PROCESS

The manufacture of ceramic products consists of the following ordered steps of activities: (1) preparation of slip, (2) casting slip in a mold, (3) drying the slip and removing the mold, (4) spray glazing the dried product, (5) firing the glazed product, and (6) inspection of the finished product. Step 2 of the process is slip casting, where a suspension (the slip) is poured into a casting mold and the liquid phase is separated by capillary phenomena, leaving a solid piece that takes the shape of the mold (Lambe 1958). The primary causal factor for cast fractures and/or deformities that cause product waste is the distribution of moisture content inside the cast before firing. When the moisture differential, or moisture gradient, inside the wall of the cast is too steep, it results in stress differences that cause the piece to deform and eventually fracture. In order to have a good cast, and therefore a solid, durable product, the moisture gradient should be as uniform as possible. A poor quality cast may sometimes be reworked by retrofitting the cracked or deformed cast to the beginning of the process. Although the raw material (clay) is saved and reused, the considerable labor and overhead involved are irretrievably wasted. Currently, more than 30% of the products at this manufacturer must be junked or reworked.

Although there have been a few computer aided improvements in the slip casting process, such as an expert system aimed at slip particle effects (Dinger 1990), it still remains basically an art. This is because there are no analytical descriptions of casting dynamics, it is affected by many human and nonhuman variables, and the effect of the interdependencies of these variables are only manifested at the end of the process, after the firing of the cast. This latent manifestation causes wasted product. This provided the motivation for the project to develop a predictive model of the ceramic casting process which would allow the manufacturer to optimize controllable process settings without wasteful and time consuming test casts. Figures 2 and 3 show the system architecture currently under development.

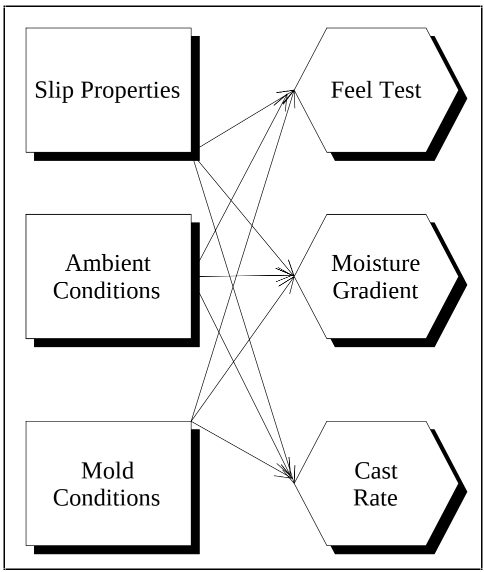

Figure 2. System Architecture - Model 1.

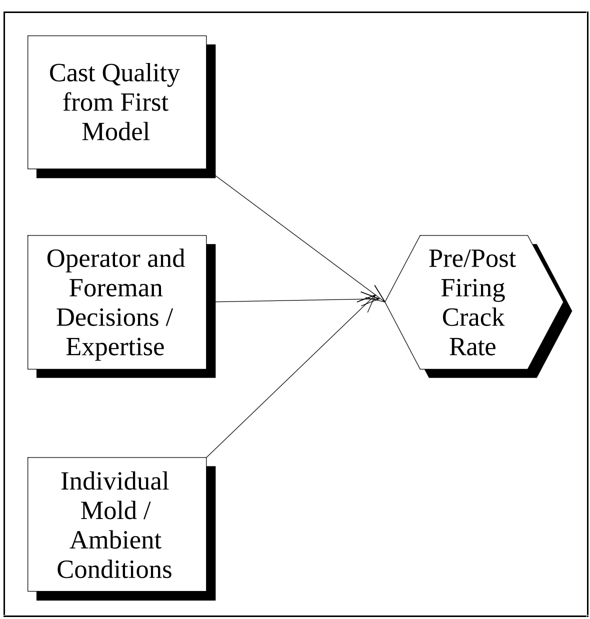

Figure 3. System Architecture - Model 2.

The quality of the cast depends on the chemical properties of the slip, the ambient conditions in the plant and the mold conditions. Ceramic engineers run a series of tests that emulate the behavior of the slip during casting. On the basis of these tests the engineers can modify the slip's composition to come up with a "forgiving" slip. An ideal forgiving slip compensates for the effects of other, less changeable, variables involved in slip casting including environmental conditions and mold conditions. The manufacturer routinely measured 19 slip property variables, 2 environmental variables and 1 mold condition variable. These are named and defined in Table 1.

DESIGN OF EXPERIMENTS (DOE) PLANS

It is important to perform designed experiments because available process data almost always will have strong correlations within the independent variables and the available data sets do not fully populate the n-dimensional feasible region of allowable process parameters. This is particularly important when the neural network is being used to optimize a process and the optimal process settings could possibly, or even likely, fall outside of the region represented in the experiential data (although within the range of each variable individually).

DOE plans were independently developed for the wave soldering and ceramic casting operations to provide a complement to production data and to allow for robust neural network models. The experimental design strategy was common to the two applications, although the specific designs were necessarily different due to the relative amount of anticipated non-linearity and interactions of the independent variables, the ability to accurately adjust the independent variable settings, and the availability of test subjects and facilities for testing.

Wave Solder Process

For the wave soldering process, the independent variables can be classified as design parameters and process parameters. The process parameters (i.e., conveyor speeds and four pre-heater temperatures) could be fully and independently adjusted over the range of possible process levels. It was not, however, as easy to adjust the design variables with the same degree of latitude. For example, the number of ground and power planes and the cumulative component mass are both variables which can be anticipated to affect circuit card board surface temperature, but they can not be independently adjusted because there is a finite number of fixed board designs available for testing.

It was important to investigate non-linear effects for the wave soldering example, but there was an insufficient number of test subjects to support a comprehensive three-way or four-way fractional factorial design. As a compromise, a composite star experimental design was used to capture non-linear effects but with fewer test trials. The experimental design is presented in Table 2. As indicated in the table, the experimental runs were randomized. This design collects data at five different levels for each independent variable and allows for the characterization of linear effects, linear interactions and non-linear effects, but will not model any interaction effects involving the non-linear terms.

Two typical boards were selected to characterize the limits of the circuit cards being soldered. The complete experimental design was performed separately for each board. Only one replication was performed for each run.

Ceramic Casting Process

For the ceramic casting operation, a more traditional fractional factorial design, presented as Table 3, was developed. This design is a 2^{V-I} design with the ability to model two-way and three-way interactions, but no non-linear terms (without the addition of the process data). The experiments were conducted over a two day period in May of 1994. Two replications were performed for each run. The high (+) and low (-) levels were selected to characterize the range of operating conditions found in the plant. As indicated in Table 3, the SO_4 content is confounded with the day number. This was undesirable, but necessary, because it was not possible to concurrently maintain two types of slip given the constraints of the plant. Each run consisted of casting a toilet for predetermined casting time, draining the excess slip and then measuring the cast rate and the moisture gradient at three locations (front, back, well) of each toilet.

One difficulty encountered during the casting experiments was the ability to adequately control the independent variables. Certain variables, such as SO_4 content within the slip and cast time could readily be controlled. However, other variables, such as plant temperature and humidity, were more difficult to control. To characterize high (+) and low (-) temperatures, two casting stations were established, one on a second floor location directly above the kiln, where it is traditionally very hot, and a second station in a more ventilated area of the plant. As the experiments were being performed, the temperatures at the two locations naturally varied, and for certain instances, the temperature difference between high and low were not sufficient to properly model the temperature effect. To compensate for this apparent shortcoming, a second, smaller DOE was conducted in September of 1994. For this experiment, localized heaters were used to simulate the hottest conditions actually encountered at the plant.

For both the wave soldering and ceramic casting experiments, an ANOVA was conducted as a precursor to neural network modeling. The ANOVA assisted in the selection of variables and provided a lower bound on the prediction accuracy which can be anticipated from the neural network. For neural network modeling, the production data and the DOE data was pooled together. The process and DOE data are very complementary, and development of a robust model required both. For example in the wave soldering case, the production data includes a wide variety of different boards, with different characteristics, but the process settings are only varied within a relatively small n-dimensional region. The DOE data had necessarily fewer different board designs but the process settings were thoroughly altered to model non-linear and interaction effects.

NEURAL NETWORK MODEL DEVELOPMENT

Neural network models are particularly suited to controlling manufacturing processes because they are capable of modeling highly non-linear relationships with complex interactions. Backpropagation neural network models were used to model the process for both problems previously described. In each instance, the intended use of the model was to optimize the process, which requires a thorough search over all possible process settings (i.e., the model inputs) to find the best combination. This requires a robust and unbiased model. By pooling the DOE and production data, the combined data set provides the required breadth and depth within the training and test sets to assure that an unbiased neural network model will be developed.

The intended use of process control models is to minimize variability in the process, and namely, to reduce defects. For both of the processes investigated, there is a relatively high degree of unavoidable variability within the input variables, which makes it particularly difficult to maintain sufficient control.

Also, it is not prudent to model the number of defects directly as a function of the process and design variables. The processes are too complex and there is the possibility of compensatory actions during the processes based on interim data or observations, and this could not efficiently be considered with one individual model. Instead, larger models were constructed consisting of specific parametric models which could then collectively model the rate of defects.

For the wave soldering process, an initial neural network was trained to predict the temperature profile of the circuit card as it travels through the wave soldering process as a function of board design parameters (i.e., power and ground planes, heatsinks, board mass, thickness, etc.) and process settings (conveyor speed, preheater settings). The goal is to uniformly preheat the board surface to minimize the thermal shock from the solder bath. The temperature profile was characterized by mean temperature, standard deviation, localized hot and cold spots, and rate of change at selected critical times during the process. Separate models were successfully developed to predict each temperature output (Coit et al, 1994). Performance of this network is presented in Table 4. Each model had nine inputs, six hidden neurons and a single output.

A second neural network is being developed to predict the defect rate (defined as the average number of defects per connection on the board) and defect location as a function of the temperature profile outputs and the design data. Development of the model uses the experimental data recorded by the temperature probe. In the actual operating environment, the board temperatures are not monitored. Therefore, the control model will use the temperature outputs from the first network as inputs into the second neural network.

For the ceramic casting problem, a neural network was successfully developed to predict the cast rate as a function of the slip conditions (SO_4 content, filtration rate, etc.), external environment (temperature, humidity) and mold conditions. The neural network had nine inputs, two hidden layers, with ten and six hidden neurons, and a single output. It was able to predict the cast rate with a normalized RMS error of less than 0.02 on the test set. The convergence of the network during training is presented in Figure 4. The optimal network was found after 2,600 epochs. A comparison of observed vs. predicted cast rate is presented in Figure 5. Within the figure, the solid line represents the placement of data points for a perfect model (i.e., predicted = observed).

CONCLUSIONS

When using a neural network to optimize a manufacturing process, the integrity and balance of the training data set dictates the quality of the resultant model. Optimization thoroughly searches the feasible region of allowable process settings, and therefore, unbiased predictions are essential for combinations of process settings which may not have been regularly encountered during the historical operating scenarios. The use of experimental design strategies is necessary to provide the required data. The DOE data and process data are complementary to provide for robust and unbiased models.

Two manufacturing examples were modeled using neural networks. While the manufacturing processes and the specific experimental designs were different, the overall modeling procedure was similar. Development of sound models was accomplished by first defining interim surrogates or predictors of quality, and then by determining problem-specific DOE and the subsequent collection of data and neural network modeling.

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BIOGRAPHICAL SKETCHES

David W. Coit is a Ph.D. candidate at the University of Pittsburgh. He has a B.S. in Mechanical Engineering from Cornell University, an M.B.A. from Rensselaer Polytechnic Institute and an M.S.I.E. from the University of Pittsburgh. He was previously employed at IIT Research Institute where he developed reliability prediction models, and developed and implemented reliability programs for industrial companies. His research interests are reliability optimization, implementation of neural networks for manufacturing processes and heuristic optimization search algorithms.

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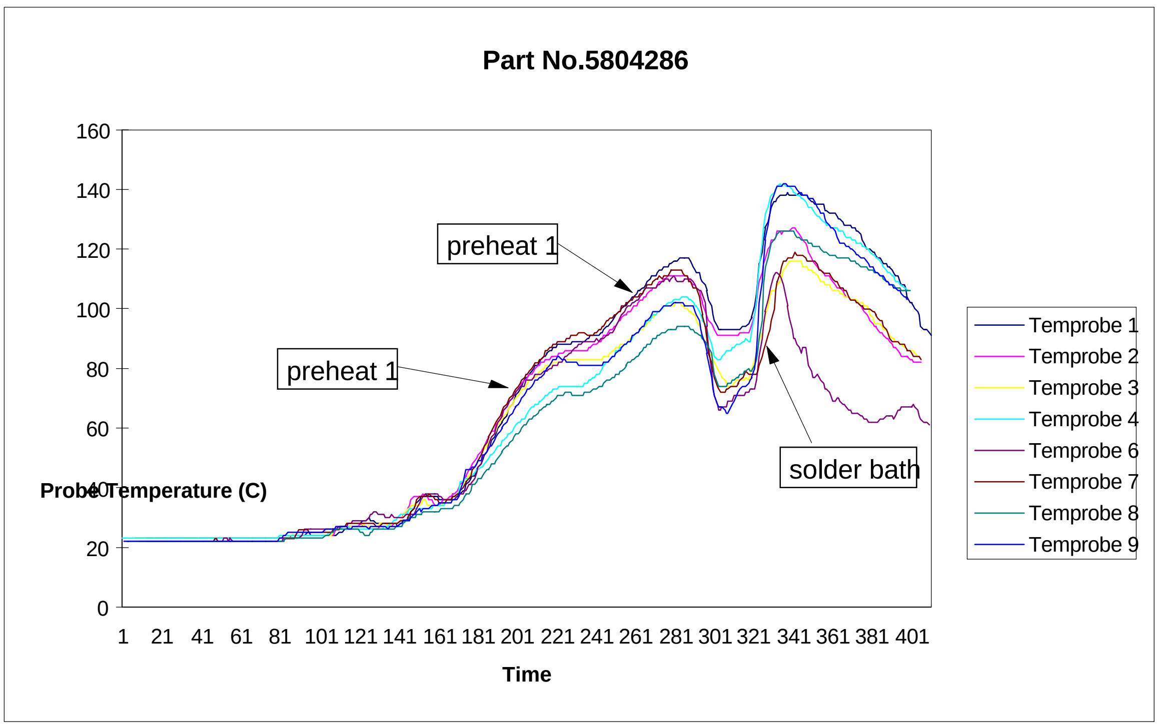

Fig 1: Thermal Profile Of The Wave Soldering Process.

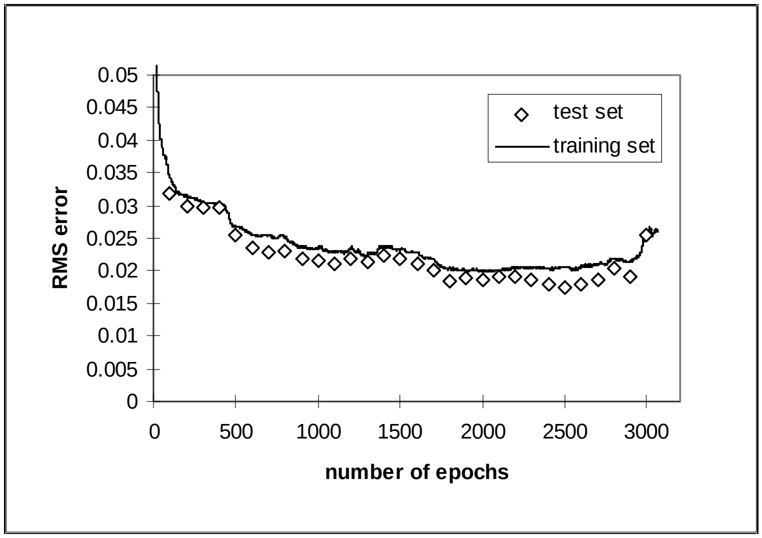

Fig 4: Neural Network Training For Ceramic Cast Rate.

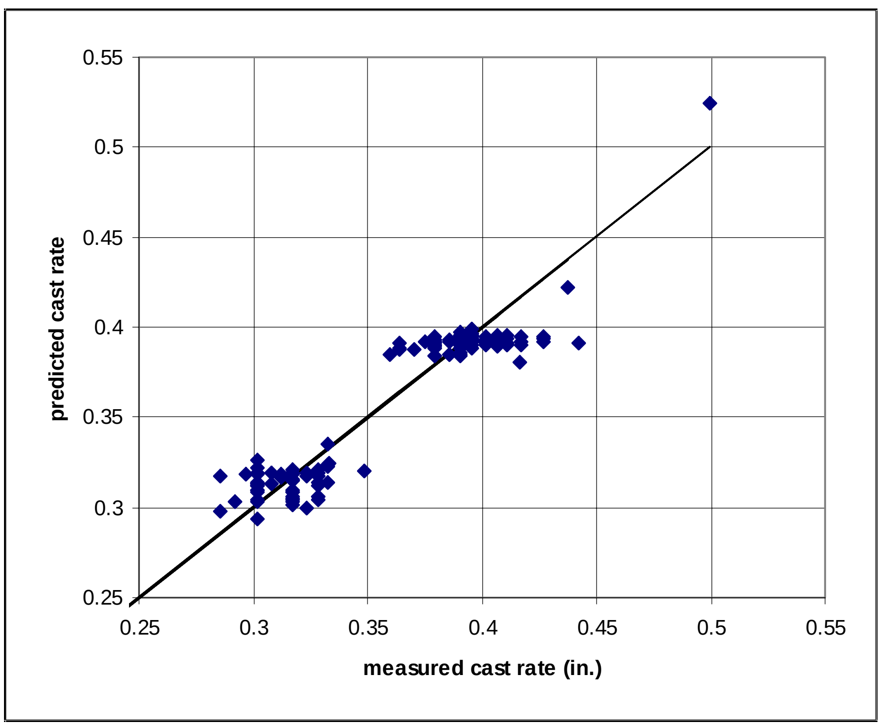

Fig. 5: Neural Network Prediction Performance.

Table 1. Slip Casting Parameters**.**

PARAMETER	WHAT DOES IT MEASURE?	HOW IS IT MEASURED?
SLIP PROPERTIES		
Test Cast 50 min. thickness in 1/32".	An approximation of the casting rate for the 50 minute test cast.	After 50 minutes one of the test casts is released of its mold and the thickness of the cast's wall is measured.
Test Cast 75 min. thickness in 1/32".	An approximation of the casting rate for the 75 minute test cast.	After 75 minutes the other test cast is released of its mold and the thickness of the cast's wall is measured.
Slip Temperature in degrees Fahrenheit.	The temperature of the slip.	Using an industrial thermometer the temperature of a sample of slip is taken.
Brookfield at 10 RPM	Viscosity of the slip at 10 revolutions per minute.	A Brookfield viscometer is turned on at 10 RPMs and after 30 seconds the reading is taken.
Brookfield at 100 RPM	Viscosity of the slip at 100 revolutions per minute.	A Brookfield viscometer is turned on at 100 RPMs and after 30 seconds the reading is taken.
Initial Reading (IR)	Change of viscosity over time. See Build Up.	Slip is aged for 3 minutes in the viscometer, which is working at 10 RPMs, and the reading is taken.
Build Up (BU)	Change of viscosity over time. See Initial Reading.	The same slip used for the Initial Reading is aged for 18 minutes in the viscometer, and the reading is taken.
Filtrate Rate	The rate at which the slip filtrates	Measures the rate of release of water from cast slip over a 20 min period.
20 minute Gelation	Gelation behavior of the slip.	The viscometer works at 1/2 RPM for 20 minutes, then the reading is taken.
Flow of slip in seconds.	Viscosity measured as ease of flow.	Time the period it takes a sample of 100 ml. of slip to flow out from a Marriot tube.
Slip Specific Gravity in grams/milliliter.	Proportion of solids in the slip.	A sample of slip is centrifuged, so the solids would settle in the bottom of the container. The proportion of solids to the total is measured.
Slip Cake Weight in grams.	Approximation of the cast rate without considering a mold.	A sample of slip is poured into a filter press. Air pressure is applied at 46 psi for 20 minutes. The filter blocks the solid particles from getting out of the press. The leftover cake is weighted.
Cake Weight Water Retention in grams.	Moisture content of the cake. See slip cake weight.	The cake from the previous test is dried and the dry cake weight is taken. From the previous test the difference in weight is made up by the moisture content.
Casting Agitator Sieve 325 Mesh in grams.	Rough estimate of the particle size of the slip.	100 ml. of slip are dump over a fine mesh (325M). The mesh is flushed and the residue is weighed.
SO_4 Reading from the Casting Agitator in ppm.	Proportion of soluble sulfates in the slip.	The proportion (parts per million) of sulfates is measured on the casting agitator (CA). The CA is where the slip is mixed.
PLANT CONDITIONS		
Temperature degrees F.	The temperature of the plant.	Measure the plant temperature with an industrial thermometer.
Relative Humidity %.	The humidity level of the plant.	Measure the RH of the plant.
MOLD CONDITIONS		
Day of the Week.	Rough estimate of the moisture retention of the test molds.	The molds tend to retain more moisture by the end of the working week than at the beginning of it.
OUTPUT PARAMETERS (QUALITY INDICATORS)		
Cast Rate	Inches of cast build up during a specified time interval, 50-70 min.	The cast thickness is measured with a ruler after removal of the mold.
Moisture Gradient.	Quantitative measure of the moisture differential in a cast wall.	The ceramics engineer takes a cut of the wall of the test cast. The engineer makes a longitudinal cut of the wall ending with two halves. The proportion of moisture content of the two pieces is computed, and their difference represents the moisture gradient.

Table 2: Experimental Design For The Wave Soldering Process.

preheat 1	preheat 2	preheat 3	preheat 4	speed	run
-1.664	0	0	0	0	26
-1	-1	-1	1	-1	5
-1	-1	-1	-1	1	19
-1	-1	1	1	1	21
-1	-1	1	-1	-1	23
-1	1	-1	-1	-1	7
-1	1	-1	1	1	16
-1	1	1	1	-1	3
-1	1	1	-1	1	4
0	-1.664	0	0	0	25
0	0	-1.664	0	0	6
0	0	0	-1.664	0	22
0	0	0	0	-1.664	13
0	0	0	0	0	1
0	0	0	0	0	15
0	0	0	0	1.664	11
0	0	0	1.664	0	2
0	0	1.664	0	0	17
0	1.664	0	0	0	9
1	-1	-1	1	1	10
1	-1	-1	-1	-1	24
1	-1	1	1	-1	12
1	-1	1	-1	1	28
1	1	-1	-1	1	8
1	1	-1	1	-1	20
1	1	1	-1	-1	14
1	1	1	1	1	27
1.664	0	0	0	0	18
preheat:	-1.664	= 400F	speed:	-1.664 =	1.4 ft/m
	-1	= 460F		-1 =	1.8 ft/m
	0	= 550F		0 =	2.2 ft/m
	1	= 640F		1 =	2.6 ft/m
	1.664	= 700F		1.664 =	3.0 ft/m

Table 3: Experimental Design For The Ceramic Casting Process.

day number	SO_4 content	relative humidity	plant temp.	cast time	mold weight	run number
1	+	+	+	+	+	5
1	+	+	+	-	+	3
1	+	+	-	+	-	4
1	+	+	-	-	-	2
1	+	-	+	+	-	8
1	+	-	+	-	-	7
1	+	-	-	+	+	1
1	+	-	-	-	+	6
2	-	+	+	+	-	14
2	-	+	+	-	-	16
2	-	+	-	+	+	12
2	-	+	-	-	+	9
2	-	-	+	+	+	10
2	-	-	+	-	+	15
2	-	-	-	+	-	13
2	-	-	-	-	-	11

Table 4: Neural Network Performance For Predicting Circuit Card Temperatures.

Output	**Mean**	**Training Set**		**Test Set**		**Entire Data Set**	
	Value	**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.