Reducing Waste in Casting with a Predictive Neural Model

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Abstract

This paper describes an interactive neural network model that predicts the quality of cast ceramic products using multiple quantitative and qualitative inputs. This has been done to enable a major sanitary ware manufacturer to reduce product waste by better control of the slip casting process. The input variables describe the raw materials, ambient conditions and line settings for the ceramic casting process. The neural network predictive model assigns one of seven quality categories to the cast based on the input data. This prediction is used by the quality control engineer to make a priori adjustments to materials and line settings so that a good quality cast is produced without trial and error. The neural model can also be used to determine optimum settings of each adjustable input variable in light of values of non-adjustable input variables.

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Abstract

This paper describes an interactive neural network model that predicts the quality of cast ceramic products using multiple quantitative and qualitative inputs. This has been done to enable a major sanitary ware manufacturer to reduce product waste by better control of the slip casting process. The input variables describe the raw materials, ambient conditions and line settings for the ceramic casting process. The neural network predictive model assigns one of seven quality categories to the cast based on the input data. This prediction is used by the quality control engineer to make a priori adjustments to materials and line settings so that a good quality cast is produced without trial and error. The neural model can also be used to determine optimum settings of each adjustable input variable in light of values of non-adjustable input variables.

1 Introduction

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. This piece is later glazed and fired inside a kiln. 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 non-human 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.

The primary 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 differentials 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 identified before firing may be recycled by retrofitting the cracked or deformed cast to the beginning of the process. Although the raw material (clay) is saved and reused, the labor and overhead are irretrievable. It is more common for defects to be identified after firing, which causes complete product waste.

The moisture gradient present in the cast is a result of different interrelated parameters. There are raw material characteristics such as rheological behavior, gelation behavior, viscosity, flow, specific gravity, etc. There are the mold's conditions, such as water retention and environmental conditions. There are ambient conditions such as plant temperature and humidity. They all impact the behavior of the cast, as will be discussed in more detail in Section 2.3.

The objective of this project was to model the interrelations of all the parameters involved and make some a priori assessments on cast condition using actual data from a ceramic products manufacturer. This was aimed at reducing product waste caused by the trial and error approach to adjusting manufacturing parameters, and the latent manifestation of substandard casts. We chose a neural model for two main reasons. First, there are no known analytical models for the slip casting process. Second, there are many related stochastic variables with non-specified probability distributions. Measurements of these variables and their effects were available, but known to contain human bias and data collection imperfections.

2 The Slip Casting Process

2.1 How Casting is Achieved

As the casting takes place, the displacement of water from the slip to the mold's wall is accelerated by the effect of capillary. When water is discharged into a container the water molecules closer to the container walls "climb up" these walls due to water's surface tension. In a capillary tube the diameter of the tube is so small that the water molecules closer to the tube's walls climb higher. In slip casting, the capillary tubes formed by the casting process and the mold's pores help to drain out the water from the slip (Lambe 1958).

As more water is drained from the cast, clay particles build up against the mold forming a solid structure. If the rate of casting is too high, particle build up will be very fast and can clog the capillary tubes. Once the capillary tubes begin to become obstructed, the movement of water out of the cast becomes more difficult. The resultant cast will have a steeper moisture gradient because there will be a very wet part near the mold face and a very dry part near the drain face. This creates a bad cast, which could crack either before or after glazing and firing. This moisture differential or moisture gradient is represented in Figure 1.

INSERT FIGURE 1 HERE

2.2 Assessment of Cast Quality

The difference in moisture content, or moisture gradient, produces a difference in consistency in the walls of the cast. So far there is no computerized substitute for the considered assessment of an experienced ceramic engineer in deciding whether a particular slip has cast properly. The manufacturer we worked with estimated product quality by producing pilot casts. The engineer strips off the pilot cast, or cuts a piece from larger pilot casts, and judges plasticity by forming or working the material with his or her fingers. This is the so called "feel test." The ceramic engineer performs the feel test and then grades the quality of the pilot cast into one of seven categories (-3 to +3). These categories go from hard (-3) to good (0) to soft (+3), where the two extremes (hard and soft) represent undesirable quality of the cast. This pilot cast procedure is a human dependent, trial and error method for establishing the necessary values of the raw material parameters. Once a pilot cast of acceptable quality is obtained (a quality category near the mid point of hard and soft), the production batch is started with the same properties of the acceptable pilot product. This trial and error procedure causes waste in itself, but more importantly, if not done properly, results in whole product batches of inferior grade (too hard or too soft) products which are not recognized until post-firing. This large scale waste is impossible to recover.

2.3 Variables Impacting Cast Quality

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 we worked with routinely measured 19 slip property variables, 2 environmental variables and 1 mold condition variable. There are two quality measures - the categorical assignment from the feel test and the actual measurement of the moisture gradient. These are named and defined in Table 1.

INSERT TABLE 1 HERE

2.4 Motivation for Neural Model

Since we were dealing with relatively sparse data of multiple non-related and interrelated variables in an indeterminate stochastic relationship we turned to a model using artificial neural networks. Neural networks have been noted to act as robust nonparametric predictive models for non-linear and stochastic relationships (White 1989).

A drawback of neural networks is their imprecision relative to analytic models; however for our application the categorical measures are broad and a misclassification in an adjacent category does not carry a severe penalty. Therefore we did not need a precise model, and, indeed given the manner of data collection and category assignment, could not support a precise empirical model.

3 Overview of Artificial Neural Networks

3.1 The Artificial Neuron

Artificial neural networks are massively parallel computing mechanisms emulating the biological brain, which store intelligence in their many interconnecting weights. These variable weights hierarchically connect nodes (neurons) both in parallel and in sequence. The entire mechanism mathematically processes vector input through the network of nodes and weights, arriving at vector output. The basic building block of every neural network paradigm is a neuron with input connections and a single output value. The signal flow of the neuron's inputs, x_i, and output, o, are considered to be unidirectional.

The neuron output signal is given by the following relationship:

$$o = f(\mathbf{w}^t\mathbf{x}) \tag{1}$$

where **w** is weight vector and **x** is the input vector: The function $f(\mathbf{w}^t\mathbf{x})$ is the transfer function with its domain being the set of activation values, or *net*, of the neural network paradigm, where *net* is the scalar product computation:

$$net \equiv \mathbf{w}^t\mathbf{x}. \tag{2}$$

The physical analogy for *net* is the analog of the biological neuron's membrane potential. Transfer functions are varied, but are usually non-linear, continuous functions. The most typical transfer function is the unipolar sigmoid:

$$f(net) \equiv \frac{1}{1 + e^{(-\lambda\, net)}} \tag{3}$$

where $\lambda > 0$ is proportional to the neuron gain determining the slope of the transfer function near *net* = 0. The architecture of a typical feedforward network with a non-linear transfer function is shown in Figure 2.

INSERT FIGURE 2 HERE

<u>3.2 Training Using Backpropagation</u>

The weight matrices used in the above discussion are trained prior to the use of the neural network model, i.e. **w** transitions from a random state to a fixed equilibrium state, storing the values of the model parameters. For predictive models, a supervised training approach is usually indicated since calibrated training data is available and it is advantageous to pre-specify the desired output. Supervised training uses the input vectors **x** in conjunction with target output vectors **t**. A distance measure between the actual and the target output serves an error measure and used to correct **w** externally.

The most well known of supervised techniques is backpropagation, which adjusts initially randomized weights during training according to the steepest gradient along the error surface (Werbos 1975, Rumelhart et al. 1986). Weights are adjusted in proportion to their contribution to the output by recycling the error signal back through the layers of weights. For a sigmoidal transfer function, error signals are calculated for the output neurons 1 to K:

$$\delta_{ok} = (t_k - o_k)\,(1 - o_k)\,o_k \quad \text{for } k = 1, 2, ..., \mathrm{K} \qquad (4)$$

and the hidden layer neurons 1 to J;

$$\delta_{yi} = y_j(1 - y_j)\sum_{k=1}^{\mathrm{K}} \delta_{ok}\, w_{kj} \quad \text{for } j = 1, 2, ..., \mathrm{J} \qquad (5)$$

where $y_j \leftarrow f\,(w^t_j\,\mathbf{z})$ and **z** is the input vector to that hidden neuron.

Weights between the hidden neurons 1 to J and the output neurons 1 to K are adjusted by:

$$w_{kj} \leftarrow w_{kj} + \eta\,\delta_{ok}\,y_j \quad \text{for } k = 1, 2, ..., \mathrm{K} \text{ and } j = 1, 2, ..., \mathrm{J} \qquad (6)$$

and weights between the input neurons 1 to I and the hidden neurons 1 to J are adjusted by:

$$w_{ji} \leftarrow w_{ji} + \eta\, \delta_{yj}\, z_i \quad \text{for } j = 1, 2, ..., \text{J and } i = 1, 2, ..., \text{I} \qquad (7)$$

where η is the training rate, which is usually set between 0 and 1. It is η which determines the step size as the weights adjust to follow the error surface contour. A large η could mean quick convergence of **w** to a local minimum, however a small η causes convergence of **w** to be extremely slow. We used a dynamic η during training, as described in Section 4.3.

3.3. Predictive Neural Networks in Manufacturing

In manufacturing, work has been done to neurally relate input parameters to product variables in a predictive model. Predictive models attempt to estimate product parameters based on process conditions before product manufacture. Andersen et al. used backpropagation networks to relate input parameters (arc current, arc voltage, travel speed and wire speed) predictively to quality measures of a weld (bead width, penetration, reinforcement height and cross section area) in a laboratory experiment (Andersen et al. 1990). Okafor pursued a similar approach for estimating surface roughness and bore tolerance in milling using input variables of cutting force components, acoustic emission and spindle vibration in a moving window size of five (Okafor et al. 1990). Smith and Dagli related many input variables of a live plastic extrusion process to prediction of the lot quality with backpropagation (Smith and Dagli 1991 A). Smith used a similar approach for injection molding of brake linings to predict product quality and its variability (Smith 1993). Ben Brahim et al. used a predictive neural network to relate ceramic product design variables to product functionality, and improved performance over a non-linear regression model used for the same purpose (Ben Brahim et al. 1993).

The work in this paper differs from the above primarily in the application area - ceramic casting - and the use of the categorical output metric. Predicting quality categories caused a discrete output function considerably more complicated than the typical binary pattern classification output function, but without the properties of a smooth, continuous output function. We developed an error measure, as described in Section 5.1, to better validate this predictive categorical neural network.

4. Building the Neural Network Model

4.1 Data Preprocessing

In order to develop a neural network model, it was necessary to screen the available data provided by the manufacturer. The company keeps a log of the daily production variables described in Section 2.3. Typical raw data is shown in Table 2. The quantitative quality variable (the moisture gradient) had only been recently implemented so we focused on the categorical metric as there were 207 data points to use for training and testing, which represented slightly more than 9 months of daily measurements. The reliability of the data varied due to human judgment and measurement inexactness. For example, the data on the Flow of Slip test (in seconds) is operator dependent, since the operator uses a stop watch to perform the measurement. The output variable (the feel test category assignment) is wholly dependent on the engineer's judgment.

INSERT TABLE 2 HERE

The data was loaded into a commercial spreadsheet program where it was processed before being used in the neural network. All the numeric parameters were normalized in the range of 0.1 to 0.9 for effective handling by the unipolar sigmoid transfer function via the following procedure:

$$n_i = 0.1 + 0.8\left(\frac{x_i - x_{min}}{x_{max} - x_{min}}\right) \tag{8}$$

where n_i = the normalized value, x_i = the raw data value, x_{min}= the minimum raw data value in all the samples, and x_{max} = the maximum raw data value in all the samples. By normalizing the data, it was possible to take into account parameters that, numerically speaking, would be relatively insignificant compared to others. The reason to normalize between 0.1 to 0.9 is to allow future data to exceed historic maximum and minimum, using a 0 to 1 sigmoid transfer function in the neural net.

The day of the week was the only input parameter that was not normalized. Treatment of the day of the week was different. There were five mutually exclusive binary input categories, each category representing one day of the week. This approach assumes that the beginning of the working week always falls on Mondays. The day of the week variable was especially important to include because the cast grew successively more moist during a week after drying over the weekend.

The quality of the cast output parameter was divided into seven outputs. The categorical scale used by the ceramics engineers ranged from a -3 (Hard) category, through 0 (Good) to +3 (Soft). There were some cases where the real output fell in the middle of two categories, such as +1.5. In this case half of the weight was assigned to category +1 and the other half assigned to category +2. So instead of a true binary output, we had a ternary encoding - 0, 0.5, 1.0. Once the data was preprocessed it was ready to be used in the network training process. Figure 3 shows the inputs and outputs of our neural network model.

INSERT FIGURE 3 HERE

4.2 Topology of the Networks

The only fixed parameters of the network were the 26 input nodes (19 material variables, 2 ambient variables and 5 neurons for day of the week) and 7 output nodes (the number of quality categories); the number of hidden layers and the number of nodes in each hidden layer were varied. After experimenting with an unsuccessful one hidden layer network, we turned to two hidden layer architectures. Although only an input layer, an output layer and one hidden layer are required to model non-linear systems (Funahashi 1989, Hornik et al. 1989), it has been suggested that for analog input, a two hidden layer network is superior (Lapedes and Farber 1988, Smith and Dagli 1991 B). A network with two hidden layers (7 nodes each) was tested, but eventually the final configuration became a network with two hidden layers, 5 nodes each. The less the number of hidden nodes the better the learning space is generalized, but there must be enough hidden neurons to learn the problem, i.e. capacity of the network must be sufficient but not overfitted for the problem (see Geman et al. 1992 for a complete discussion of this bias/variance phenomenon).

4.3 Training the Neural Network

It was decided to design and develop interactive neural network simulation software with a graphical user interface that would handle training of the neural network. The software was divided into several modules. One module handled the training process of the neural net. Another module was used to test the generalization performance of the trained network. A third module was used by ceramic engineers to see the effects on the cast quality of altering the values of input variables. In this module the neural network model is called and used transparently by the user. All modules were coded in C++, using a commercial graphical user-interface and neural nets libraries. They were designed to run adequately on a low level PC platform.

In order to train and validate a neural network, it is usual to randomly divide the available data into two sets. The first set is called the training set and normally contains most of the original data when dealing with small data sets. The second set is the testing set, made up of the remaining data. Once a network is trained, the testing set is used to estimate the generalization performance of that network.

Equations 6 and 7 were modified to include the well known momentum factor (Rumelhart et al. 1986) which smooths descent along the error surface. The weight change at training step t is multiplied by a momentum constant, ω, and added to the weight change at training step $t+1$ as calculated in equations 6 (output layer weights) and 7 (hidden layer weights) to form the total weight change at $t+1$. Some researchers have had success by beginning with larger training constant values to speed initial descent, then reducing the training constants for finer search near the error surface minimum. We followed this dynamic strategy and changed the momentum factor (ω) from 0.9 to 0.4, and the learning rate (η) from 0.3 to 0.1.

An interesting phenomenon occurred while training the network. As it was explained in Section 3.2, the backpropagation paradigm is a myopic, gradient descent algorithm. One would expect that a network is best trained when the training error approaches zero,. however we observed that while using the testing set, the neural network performed better on the test set when the training error was greater than zero. In other words, when the network was left to train repeatedly on the training set and the error approached zero, the network memorized the training set. The network became an expert on the training set and it lost some ability to generalize. This is not uncommon when dealing with relatively sparse data sets, as we did here.

This overtraining problem was overcome by saving partially trained networks, and restarting training from the best generalization point during the dynamic alteration of η and ω. By saving partially trained networks, it was easy to back up in the training process if the error performance of the network on the test set declined. So, whenever a change in the training parameters η or ω was made, a copy of the network's state (i.e. the weights' values) was saved in a file. If later in the training process the network was tested and the results were worse than before a change was made, the previous state of the network was restored from a file and a different change was made. This iterative restart allowed us to obtain the best generalizing network given our training and testing sets. The results of this network are presented in the next section.

5. Results of the Neural Network Predictive Quality Model

5.1 Predictions of the Network Compared to Actual Quality Categories

We finalized a neural network that used data from January 1, 1992 through September 18, 1992. For that period there were 180 training cases plus 27 testing cases. We compared the real assessment of the quality of the cast (i.e. that assigned by the quality engineer) versus the one predicted by the neural net. The output for each category can range from 0 to 1. The category that has the highest weight indicates the qualitative assessment of the cast. In the case where two adjacent categories revealed significant weights, it was interpreted that the assessment of the quality of the cast fell between those categories.

Two error measurements were used to evaluate the performance of the network. The first was the mean of the sum of the squared errors (MSE) of the categories. This error measure is well known in neural networks for both analog and categorical data (see Twomey and Smith in press for a good discussion of MSE in different network applications). This error measurement was used in the restart training and testing procedure described in Section 4.3. MSE is defined as:

$$MSE = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m}(o_{ij} - t_{ij})^2}{n} \qquad (9)$$

where o is the output of neuron j for test vector i, t is the target output for neuron j for test vector i, n is the number of test vectors (27 in our case), and m is the number of output neurons (7 in our case).

We derived a second error metric, the absolute distance error (ADE) to quantify the normalized absolute distance from the highest activated category to the real category. This normalization was needed because in some cases the highest activated category was not equal to 1. Equation 10 describes ADE:

$$ADE = \left| \frac{\sum_{c=1}^{7}(c * o_c)}{\sum_{c=1}^{7} o_c} - c_a \right| \qquad (10)$$

where c is the category number using a scale of 1 (previously -3) to 7 (previously +3), o_c is the network output for a category c, and c_a is the number of the actual (i.e. correct) category. This error captures the true concern of this application - how far away is the predicted category from the actual category?

The MSE per test vector was 0.052, which was less than 10% on average. The mean ADE per test vector was 0.317, or less than half a category. In 24 of the test cases, the neural network was within the correct category, while for the remaining 3 test cases, the neural network predicted the adjacent category to the actual one. This precision to one category is adequate for our manufacturer to reliably ormulate an appropriate slip without the use of wasteful pilot casts.

5.2 Using the Network for a priori Slip Adjustments

Up to this point the neural network demonstrated that it could model the slip casting process quite accurately given the precision of the available data. The next phase of the project was to use the third module of the neural network software as a tool to a priori bring the quality of the product to the desired category. This is the important aspect of the research because it is with the "what if" analysis using the neural network that the quality engineer can consistently and reliably design the best slip for the given fixed parameters. This eliminates the need for trial and error pilot casts and ensures an acceptable quality level, which minimizes product waste.

The procedure is:

1. The ceramics engineer inputs the day's slip casting conditions (slip properties, plant ambient conditions and mold condition) into the neural network.

2. The neural network evaluates the given conditions and outputs its prediction on quality of the cast, i.e. one of the seven categories.

3. The ceramics engineer compares the model output to the desired quality level. If the network's quality prediction was adequate, go to step 5. If not, continue.

4. On the basis of his/her experience the quality engineer adjusts one or more of the input parameters in the neural network. Some of these parameters are fixed and some are constrained in the magnitude and direction of adjustment. Go to step 2.

5. The changes to the neural network which achieved the desired level of quality are also made on the plant floor.

Following this procedure the ceramic engineers can control the variability of the quality of the product a priori. Instead of experimenting with the actual process, they can use the neural network model to test scenarios before making any changes. So, the art of casting is still intact; because the ceramic engineers have the expertise of adjusting the process conditions, but now the neural network model becomes an inexpensive, expedient and environmentally friendly alternative to running experiments or wasting latent manifestations of unacceptable moisture differentials.

6 Concluding Remarks

Neural networks proved to be an effective technique to model the slip casting process to reduce waste caused by inferior casts. Before this model was developed, the only archetype of the relation of the casting process to the quality of the product was found in the experience of the ceramic engineers. This, naturally, is subject to human bias and inconsistencies, and requires a substantial learning curve on the part of the ceramic engineer. The neural network was able to infer the intricate interrelations of the input parameters to the qualitative assessment of a human expert. Thus, we created a neural model which matches a consistent, knowledgeable expert. Using a categorical metric inspired us to validate the trained network with the traditional MSE as well as a new error measure, ADE.

There are several interesting extensions for this work. First, a sensitivity analysis study of the parameters involved in the model would be very useful. By checking what parameters and by how much they affect the neural network model, the quality engineers could learn which input variables are significant in affecting the ultimate quality of the cast. This could result in better product quality, because it could get rid off the effect of "noisy" input parameters; in other words, parameters that may only confuse the network. Second, the neural network model can be used as a training system for ceramic engineers that get involved in the area of slip casting. A ceramic engineer who is new to the area of slip casting could use the neural network program to build his/her skills on the dynamics of slip casting since the system mimics the "best" engineer. This training aspect was particularly attractive to the manufacturer. Third, a neural network model could be developed so that it uses the moisture gradient found inside the cast as a quantitative measurement of the quality of the cast. Such a model would predict a continuous variable (the moisture gradient) using the current input parameters. This model would probably give a more reliable and precise quality assessment since it would not contain the human bias or lumpiness of the categorical measures. We are proceeding with the three extensions discussed in the preceding paragraph with the partnership of the casting manufacturer.

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Figure 1. The Moisture Gradient Between the Mold and Drain Face.

Figure 2. Generic Neural Network Components.

Figure 3. Variables of the Neural Network Predictive Model.

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 casted slip over a 20 minute 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 suspension 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.

Table 1. Slip Casting Parameters (continued).

PARAMETER	**WHAT DOES IT MEASURE?**	**HOW IS IT MEASURED?**
SLIP PROPERTIES (continued)		
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.
Particle Size Distribution.	Taken at 30mmic, 5mmic, 1mmic and 0.5mmic (4 variables).	Size of particles measured by sedimentation through 4 different sized filters.
PLANT CONDITIONS		
Temperature in degrees Fahrenheit.	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 Condition.	Qualitative assessment of the cast quality. Rough estimate of the cast moisture gradient.	An experienced ceramics engineer works a cut of the test cast with his/her fingers. The engineer grades the cast into seven categories that range from firm to good to soft.
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. Typical Raw Data from the Casting Manufacturer.

Parameters

Day of Week	Mon	Tue	Wed	Thu	Fri	Mon
Test Cast 75 min.	23.3	22.7	22.3	23	23	21.7
Test Cast 50 min.	19.3	19.3	19.3	19.7	20.3	19
Temperature	89.7	90.2	90.6	91.5	91.6	91.2
Brookfield 10 RPM	43	43	41	43	41	43
Brookfield 100 RPM	241	237	238	241	238	243
Initial Reading	103	103	99	99	98	99
Build Up	107	108	96	100	102	110
20 min. Gelation	49.2	47.3	45.4	49	45.5	50.7
Filtrate Rate	6	6	6	6.6	6.4	6.6
Slip Flow	15.6	15.6	15.6	15.6	15.8	15.8
Specific Gravity	1.834	1.834	1.834	1.834	1.834	1.834
Cake Weight	55.5	56.8	56.3	60	59.7	62
Cake H2O retention	21.12	21.06	20.24	20.47	20.61	20.39
325M Residue	60.8	68.4	60.8	57.3	68	64
Sulfates	44	50	48	56	52	38
Particle size 30 mic.	91	91	91	91	91	91
Particle size 5 mic.	50	50	50	50	50	50
Particle size 1 mic.	28.5	28.5	28.5	28.5	28.5	28.5
Particle size 0.5 mic.	21	21	21	21	21	21
Plant Temperature	82	83	88	91	92	90
Plant R.H. %	48	51	50	50	51	50
Quality of Cast	2	-1	-1	0	0	0