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This paper is a case study that describes a hybrid system integrating fuzzy logic, neural networks and algorithmic optimization **for** use in the ceramics industry. **A** prediction module estimates two quality metrics of slip-cast pieces through the simultaneous execution **of two** neural networks. A process improvement algorithm optimizes controllable process settings using the neural network prediction module in the objective function. An expert system module contains a hierarchy of two fuzzy logic rule bases. The rule bases prescribe processing times customized to individual production lines given ambient conditions, mold characteristics and the neural network predictions. This paper demonstrates the applicability of newer computational techniques to a very traditional manufacturing process and the system has been implemented at a **major** US plant.

1. Introduction

Slip-casting is used as the primary manufacturing process for many complex ceramic goods including sanitaryware, giftware, and tableware where ceramic pressing is not practical. Slip-casting is a second choice after pressing because it is considerably more difficult to achieve good results in both product quality and productivity. However, pressing can only manufacture simple shapes, such as plates, while slip-casting can manufacture items such as bowls, pitchers, statues, and sinks. The manufacture of slip-cast ceramicware consists of the following steps: (i) preparation of the slip (liquid clay); (ii) casting the slip in a plaster mold for a specified duration; (iii) removing the mold; (iv) air drying the cast piece; (v) glazing the dried product; (vi) firing the glazed product in **a** kiln; and (vii) inspection of the finished product. Of particular interest is step (ii) of the process (slip-casting), where liquid slip is poured into plaster molds and allowed to cast for a specified time period to form a solid product [1]. It is the slip-casting process that largely determines the quality of the final product, since cracks, slumps, and instabilities in the cast are manifest only subsequent to the casting process. Defects that are found before the ware is fired can often be repaired. For defects that cannot be repaired, the clay material can be recovered, but the considerable labor and overhead are still lost. Most defects that are found after firing result in a complete loss of the defective piece. The proportion of defective pieces due to casting imperfections can, according to internal industry sources that cannot be cited, approach 30%, a significant problem affecting the efficiency and profitability of slip-casting manufacturing firms. Additionally, the slip-casting step is the most time consuming and operator intensive aspect of the process.

This paper describes a modular system for the slip-casting process that integrates neural networks, a dual-objective optimization algorithm, and fuzzy logic techniques as shown in Fig. 1 to improve both the quality and efficiency of the slip-casting step. **A** hybrid approach was used because the modules can be used individually or collectively according to the decision to be made. The predictive module estimates ***cast rare*** and ***moisture gradient*** which are the two primary determinants of cast quality and efficiency, given ambient conditions, process settings and slip characteristics. The process improvement module determines the best set of controllable settings for the given ambient conditions and slip characteristics. The fuzzy logic expert system recommends the processing time customized to a production line given the localized ambient state and the condition of the plaster molds. The system also includes a data repository to store and analyze daily process records, an automatic control charting feature, and a training module to expedite the learning curve of new workers.

While these newer computational approaches have been proposed for industrial use in many papers, there

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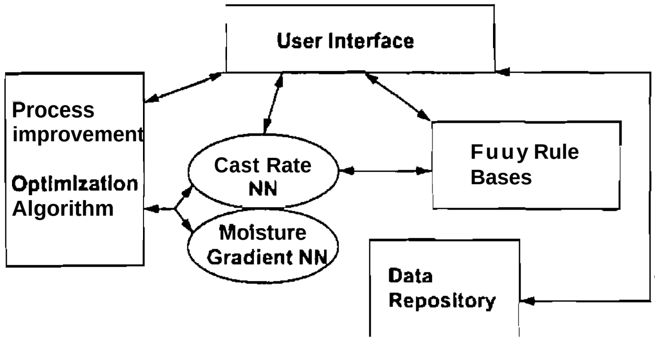

Fig. 1. Block diagram of the hierarchical system.

are few examples of implemented systems in traditional manufacturing environments. The slip-casting industry has experienced little technological improvement and still depends on human expertise and judgement, and on trial-and-error casting tests. This hybrid system is the first known intelligent decision-support system for ceramic casting. It has been implemented at a major US manufacturer of sanitaryware to enable superior product quality, reduced waste, and improved manufacturing efficiency. Section 2 describes the slip casting process and previous approaches to process improvement and control. Section 3 describes each module of the hybrid system, discussing the development effort and giving results. A summary of the general contributions of the research and the lessons learned from working on a complex traditional manufacturing process concludes the paper.

2. Background

2.1. *The slip-casting process*

The slip-casting process is used to produce ceramicware in intricate shapes that cannot be obtained through other methods, such as pressing. In the slip-casting process, a slurry, or slip, is prepared by mixing clay powder with a suspending liquid. Deflocculants are added to the slurry to provide stability and density, and binders are added to ensure that the resulting cast is strong enough to be handled. The slurry is then poured into a plaster mold. Most of the liquid in the slip is absorbed into the mold through capillary action, leaving a solid cast inside the mold. When it is estimated that the cast has reached the desired thickness and stability, the mold is removed and the piece is dried, glazed and fired [2].

The primary causal factor for cast fractures and/or deformities is the distribution of moisture content inside the cast prior to firing. When the moisture differential, or ***moisture gradient,*** through the cross-section of the cast is too steep, it results in stress differences that cause the piece to deform and to eventually fracture (often during firing). In order to have a good cast, the moisture content should be as uniform as possible through the cross-section, i.e., a moisture gradient near zero. Another important manufacturing measure is ***cast rate,*** which is actually the thickness of the cast achieved during a specified time in the mold. A larger cast rate results in quicker casts and more efficient production.

2.2. *Statics and dynamics of the slip-casting process*

The quality of the cast and the cast rate depend on the slip conditions, the ambient conditions in the plant, and the plaster mold state prior to casting. To decide on the values of the process-controllable variables each day, ceramic engineers run a series of tests that emulate the behavior of the slip during casting. On the basis of these time consuming, human-dependent, and trial-and-error tests, the engineers can obtain a "test cast" of acceptable quality. Then, a production batch is started with the same properties as the acceptable test product. Two ambient variables, 10 slip property variables and casting time (Table 1) are the relevant process parameters.

There are individual factors, however, which make uniform production impossible. These factors, which

Table 1. Slip casting process parameters

Input	*Parameter*	*Definition*
1	Plant temperature (OF)	the temperature of the plant
2	Relative humidity (%)	the humidity level of the plant
3	Cast time	the time the liquid slip is left in the mold before draining
4	Sulfate *(SO,)* content	proportion of soluble sulfates in the slip
5	Brookfield - 10 rpm	viscosity of the slip at 10 revolutions per minute
6	Brookfield - 100 rpm	viscosity of the slip at 100 revolutions per minute
7	Initial reading	initial viscosity (taken at 3.5 minutes)
8	Build up	change in viscosity from initial reading (taken after 18 minutes)
9	20 minute gelation	thixotropy (viscosity versus time)
10	Filtrate rate	the rate at which the slip filtrates
11	Slip cake weight	approximation of the cast rate without considering a mold
12	Cake weight water retention	moisture content of the cake, see slip cake weight
13	Slip temperature	the temperature of the slip

change over time and among operators, are: localized ambient conditions of the production line and the state of the plaster molds. An overall decision on casting time is made by the ceramic engineers, and then customized to an individual production line (30 to 40 molds) using the ad *hoc* judgment of the foremen or operators. The primary determinants of mold state are the age of the mold and the localized ambient conditions. As the age of a mold increases, its capillary action degrades, which causes an increase in the required casting time. Molds that are cast under hot, dry ambient conditions (i.e., near a kiln) require less casting time than molds cast under cooler, wetter conditions (i.e., near the building exterior). The variance of ambient conditions across the plant can be a significant problem in ceramic casting facilities, which are large and not environmentally well controlled.

2.3. *Previous relevant work*

Previous work in ceramic process optimization has been very limited due to the inability of theoretic and analytic models to adequately describe the complex dynamics of the casting process. Readey [3] has introduced a process optimization method using a graphic format to improve manufacturing yields for ceramics by considering a small subset of the process variables. He decided that the analysis would become too complex if more than a few process variables were considered. Knotts [4] has used statistical experimental design to select optimum ball clays (a raw material) for increasing casting rates in a sanitaryware application. Dinger [5] has developed a rule-based expert system to examine the effects of particle size distribution on slip rheology. Stinson *et al.* [6] have applied neural networks to laser scatter patterns to characterize the microstructure of optical translucent ceramics. Martinez *et al.* [7] have used a neural network to predict cast quality using a categorical metric. Xia *et al.* [8] have constructed a materials design system, which includes a ceramics database, optimization modules, a knowledge base and an artificial neural network, to improve generic properties of ceramics.

Several studies on the application of hybrid systems using fuzzy logic and/or neural networks in manufacturing have been conducted. Lin *et al.* [9] have applied a backpropagation neural network to identify the system model for evaluating a fuzzy logic controller of a cement roller mill. Shin and Vishnupad [10] have presented a generic scheme for intelligent optimization and control of complex manufacturing processes. They proposed using neural networks to model the nonlinear process and then using fuzzy logic for process control. Chen *et al.* [11] have discussed the hierarchical use of two neural networks for copolymer composition distribution predictive control. A critical parameter is identified by the first neural network, which is then fed to the second network for control. Azouzi and Guillot [12] have presented an adaptive neurocontrol scheme for on-line optimization of machining. Their method uses a hybrid neural network that learns the relationships between process inputs and process states both off-line and on-line.

3. Development of the hybrid integrated system

This section starts with the data repository, then follows with a description of the modules for neural network prediction, process improvement, and cast time customized to each production line.

3.1. *Data repository and training module*

The data repository is a large relational database that includes the daily parameters of Table 1 describing ambient conditions, process settings and slip characteristics. The outcome variables of moisture gradient and cast rate, as measured from the test cast, are also stored. The database consists primarily of production data supplemented with a few well chosen experiments to provide observations on the extremes of the production environment (e.g., very high or low temperature [13]). The user can visualize data (for each parameter) as Shewhart control charts [14] or as scatterplots over any specified time period. Both manners of presenting the data have been valuable to plant personnel because there is considerable short-term variability that masks long-term trends when examining only a few weeks of data (as was previously done). This daily data is also used as input to the remaining modules. While this might be relatively uninteresting from a research perspective, the compilation, purification and structuring of this database was a significant effort and one that affords the plant real benefits in the ability to analyze their casting process over both the long run and the short run. A training module has been included in the system and consists of 10 archetype (good, average and poor) casting days from the data repository. This allows novice engineers, foremen, and operators to interact with typical casting days to try to improve results by virtually altering process variables interactively with the system. The plant was especially interested in this feature as the learning curve for slip-casting is long and casting results are strongly dependent on experiential knowledge.

3.2. *Neural network prediction module*

The following facts motivated the development of two separate but parallel neural networks – the Cast Rate Neural Network (CRNN) and the Moisture Gradient Neural Network (MGNN) (see Fig. 2): many of the process variables are uncontrollable (for instance, ambient conditions and particle distribution of the raw material), most slip properties cannot be changed on a day-to-day basis, and the interactive behavior of the process variables is mostly unquantified. The neural net-

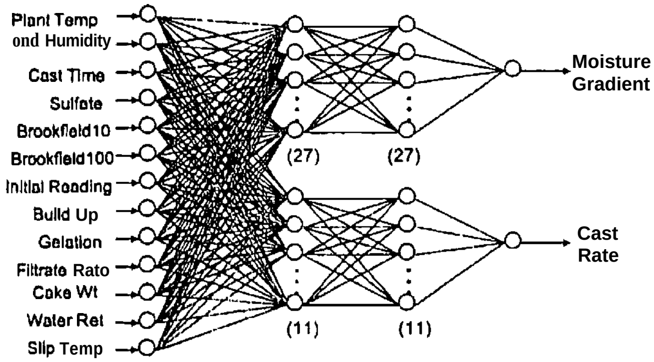

Fig. 2. Neural network prediction module.

work is an empirical universal approximator, that is, a neural network theoretically can model any relationship solely through examination of the inputs [15,16]. Neural networks have been used in many manufacturing applications (see Zhang and Huang [17] for a good overview) and have been noted to be robust to imperfections in the data and accommodating of large dimensional data sets. These attributes were especially important to this application, where the form **of** the relationship between the many process variables and cast quality was undefined and where the data set available from production contained missing and corrupt observations. The neural network predictions can be used alone as surrogates for the daily physical test casts; the predictions are also used in conjunction with the process improvement algorithm and with the expert system for production line control.

3.2.1. *Neural network architecture and training*

The data sets available contained 952 observations **(—3.5** years) for the **CRNN** and **367** observations (—1.5 years) for the **MGNN.** Moisture gradient is a difficult measure to make on a daily basis and so it had been enacted more recently in the plant than' the easier daily cast rate measurement. The neural network architectures, training parameters, and stopping criteria were selected through experimentation and examination of preliminary networks. An ordinary backpropagation learning algorithm was used because of its documented ability as a continuous function approximator [15,16].

The final network architecture used for the **CRNN** was a multi-layered fully-connected perceptron with **13** inputs, two hidden layers with 11 hidden neurons in each layer, and a single output (the cast rate in inches). The **MGNN** model was developed in a similar way using the same input variables, two hidden layers with 27 hidden neurons in each layer, and a single output (moisture gradient in percent change).

3.2.2. *Neural network Validation procedure*

The more traditional random separation (***data splitting***) of the data into **a** testing set and a training set (e.g., 20%, 80% respectively) was not used. This was because the system was built for industrial use and the plant engineers and supervisors ***had to be assured*** that the neural network predictions were accurate. Therefore, a five-fold group ***cross validation*** was used to validate the neural networks as this allows all data to be used for both validation and construction of the neural network prediction models. This cross-validation method, although intensive in computational effort, leverages the data by using all observations for both training and testing [18–21]. The estimate ***of*** neural network prediction error is nearly unbiased and is more reliable than that obtained from the data splitting method [22]. Furthermore, the final neural networks used in the system are constructed using ***all*** the data rather than a training subset, ensuring the best possible prediction performance.

The available data for each neural network was divided into five mutually exclusive groups using systematic sampling after randomizing the entire data set. For both the **CRNN** and the **MGNN,** five validation networks with parameters identical to those of the final models described in Section **3.2.1** were built, each using four groups of the data as a training set, and the remaining group as a test set. In other words, each cross-validated network was trained using **80%** of the available data and tested on the remaining **20%.** Combining these five mutually-exclusive test sets would give the original available data set. The errors of the five testing sets provide the estimate of the generalization ability of the final network.

3.2.3. *Results 'discussion*

3.2.3.1.*CRNN.* Figure 3 shows a typical cross-validation network and its predictions on the 20% test set against the observed cast rate. In examining the results over the five cross-validated networks, it was verified that the CRNN performed well on all the available data (952 observations) and had unbiased generalization for all combinations and values of the independent variables used in this application. The summation of the test sets over the five validation networks showed a Mean Absolute Error (MAE) of **0.017 (4.84%)** and **a** Root Mean Square Error **(RMSE)** of **0.024 (6.83%).** These values were precise enough for plant use.

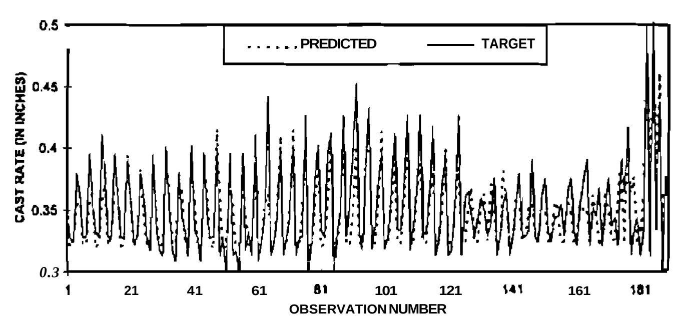

Fig. 3. Performance on a **20% cross** validation: predicted against target cast rate.

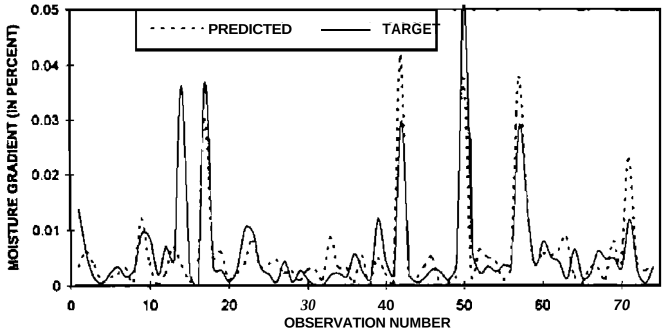

Fig. 4. Performance on **a** 20% cross validation: predicted against target moisture gradient.

3.2.3.2. ***MGNN.*** Similar analysis of each 20% holdback test set showed that the **MGNN** performed fairly well across all the available data **(367** observations). Figure **4** shows the predictions of the **MGNN** against the observed moisture gradient for one of the **20%** holdback test sets. The summary of the five test sets were an **MAE** of **0.0036 (68.64%)** and an **RMSE** of 0.0061 (I **16.30%).** The reduced precision of the **MGNN** was due to several factors. A smaller sample of data was available than for the CRNN and there was considerable human error possible in the moisture gradient measurement. This imprecision, however, did not preclude the use of **MGNN** in the system. **To** understand why, Table 2 shows the MAE, **RMSE** and percentage correct for five ranges of moisture gradient whereas Table **3** shows the distribution of incorrect predictions **(for** the test sets). The **MGNN** does a fairly good job of prediction for small moisture gradients, and can discriminate between a good moisture gradient and a bad moisture gradient since nearly all errors are only a category prediction away. Taking a categorical approach, the MGNN had prediction ability of adequate precision for use in the plant.

3.3. Process improvement module

This feature recommends settings **of** controllable variables, given fixed settings of the other process variables, to maximize quality and productivity. The variables most commonly altered on a daily basis are ***sulfate content*** and ***casting time***. An enumerative optimization algorithm sequentially generates all possible combinations of casting time and sulfate content on a discretized lattice of **26** by **26** bounded by the production extreme values. The combinations of sulfate content and casting time are sent to the neural network prediction module along with that day's values of the uncontrollable, or state, process variables. Enumeration is used because the search space is relatively small and the process cannot support settings finer than the lattice used (e.g., casting time is not specified in units smaller than a minute). If the search space were larger, a more efficient optimization routine could be used such as Newton's method (handling the optimization problem as continuous [23]) or simulated annealing (handling the optimization problem as combinatorial [24]).

The neural network prediction module estimates the cast rate and the moisture gradient for each combination. The optimization algorithm selects the best three combinations that minimize the moisture gradient (primary objective) and maximize the cast rate (secondary objective). Providing the three best process settings **allows** the ceramic engineer to review the options prior to implementation, maintaining some human expertise in the decision. If the user wished to further study the three recommended settings by considering other factors, he or she could use a method such as the Analytic Hierarchy Process [25].

3.4. *Fuzzy logic expert system module*

This module incorporated important factors affecting cast quality that are individual to a particular production line, **as** detailed in Petri and Smith [26]. These factors are the age of the plaster molds (which ranges **from** 0 to **6** weeks) and the ambient conditions of where the line is located in the plant. **It** was necessary to use a knowledge-based approach rather than a pure numeric model because there was no data that related mold age and local ambient environment to cast quality, and it was impractical to begin to record such data in the plant. Instead, these two important factors were included in two rule bases that work as a hierarchy as shown in Fig. **5.** The

Table 2. MAE, RMSE and percent correct of MGNN

Category	*Moisture gradient range*	*Number of observations*	*Number of correcl predictions*	*Percent correct* (%)	*MAE*	*RMSE*
I	<0.005	272	220	80.88	0.001 904	0.002 641
2	0.005–0.010	53	23	43.40	0.002 243	0.002 817
3	**0.01**0–0.020	24	**14**	58.33	0.003 952	0.004 758
4	0.020-0.030	***9***	**6**	66.67	0.004 978	0.006 430
5	>0.030	**9**	5	55.56	0.015 **485**	0.021 **231**

Table 3. Distribution of incorrect predictions of MGNN

Number of categories away	*Number of observations*
1	89
2	9
3	1
4	0

rule bases replicate the knowledge of the ceramic engineers, foremen and operators at the manufacturing facility, and provide cast time decisions customized for a specific operator's line of **30** to **40** molds. All molds of a given production line are the same age and located in the same place in the plant, therefore, they are of the same state. The use of fuzzy logic was included to allow for more precise handling of the variables, reduce the number of rules required, and result in a smoother decision surface.

Ambient temperature ("F), ambient relative humidity (%), and the age of the molds in weeks for that production line are presented as crisp, continuous inputs to the first fuzzy rule base that predicts mold condition. Mold condition is rated on an ordinal scale of zero to 10, with zero being the driest and 10 being the wettest. This prediction of mold condition is then paired with a crisp, continuous prediction of the cast rate from the **CRNN;** together these are used in the second fuzzy rule base in order to generate a recommended cast time in minutes for that particular production line. Defuzzification to a crisp output is done using the centroid method by computing the center of mass of the region of the output variable defined by the fuzzy output [27].

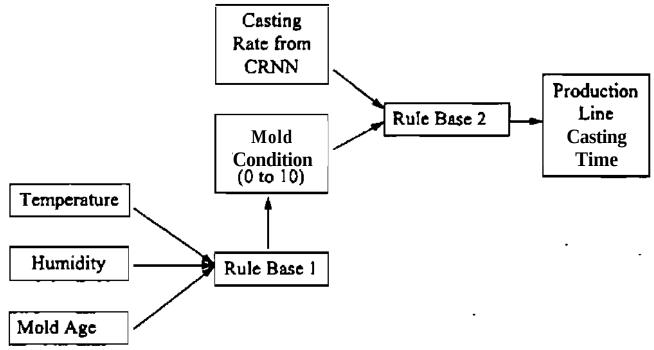

Fig. 5. Structure of the fuzzy logic expert system module.

3.4.1. *Development of the rule bases and the membership functions*

Three ceramic engineers were asked to develop rule bases for both mold condition and cast time independently of each other. A comparison of the three rule bases was then provided to each of the ceramic engineers, and they were given the opportunity to modify their responses, a simple Delphi technique. The three updated rule bases were consolidated into a single rule base. Tables **4** and **5** show the Fuzzy Associative Memories (FAM's) for each rule base. For example, Table **4** shows that if the ambient ***temperature*** is ***low***, the ambient ***humidity*** is ***high***, and the ***mold age*** is *old*, then the ***mold condition*** is ***very wet.***

The membership functions for the ambient temperature, ambient humidity and cast rate were developed through examining the frequency distributions of approximately 2 years of historical plant data. Each **of** these membership functions used three trapezoidal fuzzy sets (examples are shown in Fig. *6)***.** The membership functions for mold age, mold condition and cast time were

Table 4. FAM for mold condition

Temperature	*Humidity/age*								
	Low			*Medium*			*High*		
	New	*Mid*	*Old*	*New*	*Mid*	*Old*	*New*	*Mid*	*Old*
Low	Dry	Dry	AvgWet	Avg	AvgWet	VeryWet	AvgWet	Wet	VeryWet
Medium	VeryDry	Dry	AvgWet	Dry	Avg	Wet	AvgDry	AvgWet	VeryWet
High	VeryDry	VeryDry	Avg	VeryDry	Dry	AvgWet	AvgDry	AvgWet	Wet

Table 5. FAM for cast time

Cast rate	*Mold condition*						
	VeryDry	*Dry*	*AvgDry*	*Average*	*Avg Wet*	*Wet*	*Very Wet*
Low	Avg	Short	AvgShort	Avg	AvgLong	Long	Longest
Medium	Short	Short	AvgShort	Avg	AvgLong	Long	Long
High	Shortest	Shortest	Short	Short	AvgShort	Avg	AvgLong

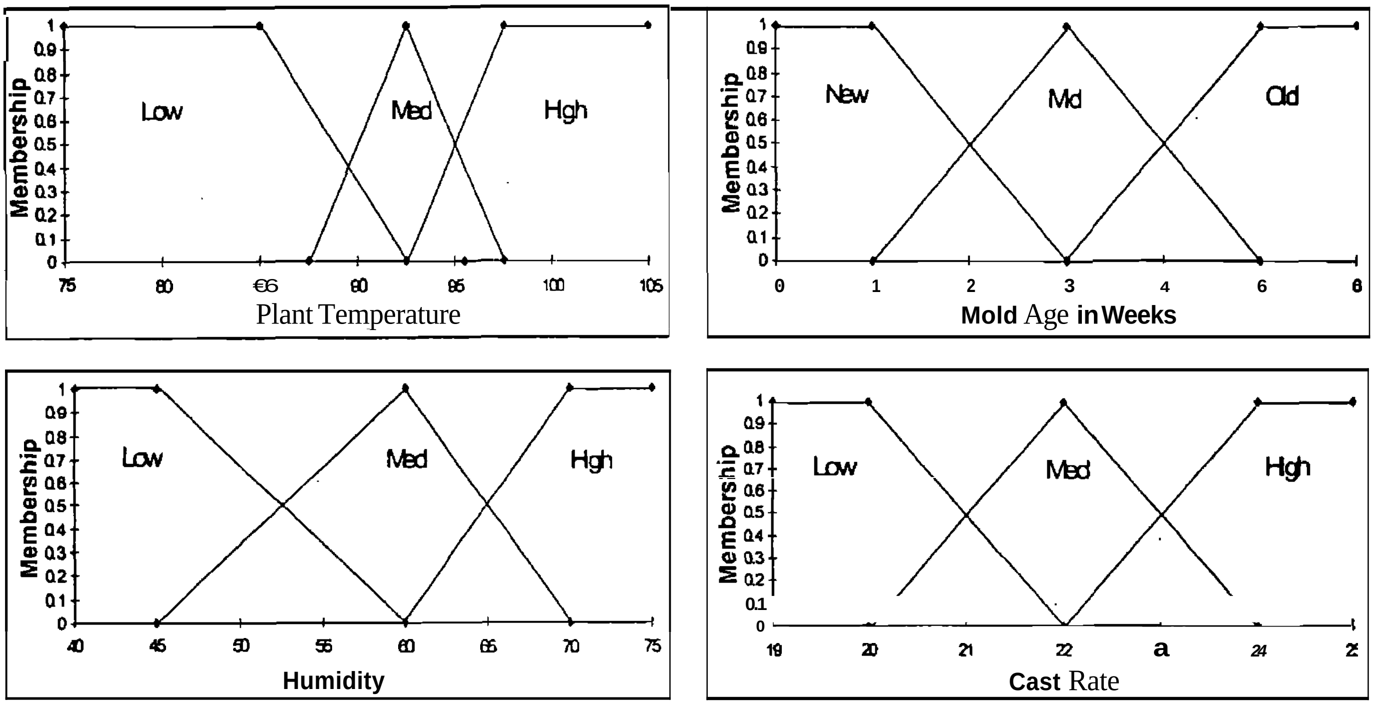

Fig. 6. Some **of** the membership functions in **the fuzzy** expert system.

developed in conjunction with the plant's ceramic engineers since data was not available. The number and shape of the trapezoidal fuzzy sets for mold condition and cast time were set by the ceramic engineers in order to incorporate the full range of process dynamics.

Figure 7 shows a decision surface for the cast time rule base. Here the x-axis is the cast rate, the y-axis is the mold condition, and the z-axis is the recommendation for cast time for the production line. Note that the decision surface is clearly non-linear yet has smooth transitions

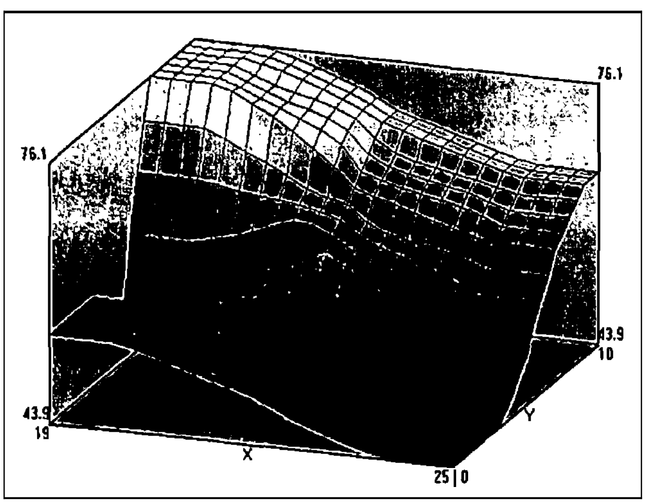

Fig. 7. Decision **surface for** cast time rule base **with** cast time (in minutes) (z) **versus** cast rate **(in** inches) (x) and mold condition (ordinal scale) (y).

between decision states. Smoothness is a property of fuzzy rule-based systems not often achieved in standard rule bases unless a great many rules are used.

3.5. *System platform*

This system does not require any special hardware platform other than the standard **WINDOWS** environment on a PC. **Pull** down menuing and windowing capabilities are supplied by Visual Basic to provide a familiar interface to the user. The system requires no special user expertise to implement or use the system. This was done purposefully to accommodate the limited computing facilities in the plant and the variety of users. Visual Basic provides the user interface and the integration architecture. The data repository was built in Microsoft **Access.** The neural network models were developed using Brainmaker Professional, a neural network development **soft**ware package, and the completed models were translated to compiled **ANSI *C*** code. The optimization algorithm was developed and compiled in C. The fuzzy logic rule bases were developed using Togai Infralogic's TILShell software package, version 3.0.1. The expert system was then compiled into a **DOS** executable file using the package's ***C*** code generation capabilities.

4. Conclusions

This hybrid modular system is the first known comprehensive decision support system using computational intelligence for the ceramic slip-casting process. The integration of neural networks, an optimization algorithm and the fuzzy logic rule bases allow modeling of the highly non-linear relationship among the process variables and the capture of qualitative factors and expert knowledge from plant personnel. Utilization of the system enables casting decisions to be made consistently and correctly without the need for judgmental speculation or expensive trial-and-error test casts. This case study demonstrates that the newer computational approaches can be of value even in what have traditionally been regarded as "low tech" processes, such as slip-casting. This system does not require any special hardware or software, or any particular expertise on the part of the user. In fact, the technologies behind the system have purposefully been kept hidden from the user.

From a generic hybrid systems viewpoint, the most interesting aspect of this research is that the three approaches work in a truly integrative manner. The neural networks serve as both an objective function evaluator for the optimization algorithm and as an estimator of an input needed by the fuzzy rule base. Because of the dependence of the system on the neural network predictions, validation was as stringent as possible. The users had to be assured that the predictions of cast rate and moisture gradient were sufficiently accurate over the range of operation of the plant. This was accomplished through empirical validation using the group cross validation method so that all data contributed to both the final predictive models and the validation effort.

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