A Hierarchical Fuzzy Model for Predicting Casting Time in a Slip-Casting Process*

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Abstract

This paper outlines the development of a predictive model for the casting time in a ceramic slip-casting process. The predictive model was developed through a hierarchy of two fuzzy logic rule bases: one that predicts the condition of a mold based on the ambient temperature and humidity and the age of the mold, and one that predicts casting time based on the casting rate of the slip and the condition of the mold. This system is currently being implemented at a major sanitary ware manufacturing facility.

1. Introduction

In the slip-casting process, liquid slip is poured into molds and allowed to cast for a specified time period. The green ware is then removed from the molds, dried, glazed, and fired. It is the slip-casting process that largely determines the quality of the final product, since cracks, slumps, and instabilities in the cast can manifest themselves at any time after the casting process. Defects that are found before the ware is fired can often be repaired. For those defects that cannot be repaired, the material can be recovered and reused in the process, but the associated labor and overhead are still irretrievably lost. Most defects that are found after firing result in a complete loss of the material, the labor, and the overhead. Many ceramic ware facilities produce up to thirty percent scrap and rework.

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This paper focuses on the development of a predictive model for the casting time of the slip-casting process using fuzzy logic techniques. Fuzzy logic was selected for several reasons. First, there are no known analytical models to determine the appropriate casting time for the process. Second, fuzzy logic allows expert knowledge from ceramic engineers, foremen, and casters to be incorporated directly into the process model. Third, fuzzy logic models are not developed through strictly empirical techniques, therefore variables that do not have the benefit of a rich historical data set can still be used in the model.

2. Background

2.1 The Slip-Casting Process

The slip-casting process is used to produce ceramic ware in intricate shapes that cannot be obtained through other methods such as pressing. In the slip-casting process, a slurry is prepared containing clay powder in a suspending liquid such as water. 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. This slurry, or slip, is then poured into a plaster mold. The liquid in the slip is absorbed into the mold through capillary action, leaving a solid cast inside the mold. When the cast has reached the desired wall thickness, it is removed from the mold, dried, glazed, and then fired to produce a finished product.[1]

The casting time, or the amount of time the slip is left in the mold, is usually set through the use of a test cast. A test cast is poured and allowed to cast for a pre-specified amount of time. The cast is then removed from the mold, and the wall thickness is measured. Once a test cast of acceptable quality is obtained, the production batch is started with the same properties as the acceptable test product (e.g. proportion of deflocculants and binders in the slip). There are individual factors, however, that make uniform production of the casts impossible. These factors, which change over time and among operators, are ambient temperature and humidity, age and condition of the mold, and casting time. An overall decision on casting time is typically made by a plant's ceramic engineers and is then customized to an individual casting line, typically containing approximately thirty molds, by the foremen in an ad hoc basis.

The primary determinants of the mold condition are the age of the mold and the ambient conditions. As the age of the mold increases, the capillary action of the mold degrades. The mold becomes saturated with water, causing an increase in the required casting time. Ambient conditions also have a significant effect on casting time. Molds that are cast under hot, dry conditions require less casting time than molds cast under cooler, wetter conditions. The effects of ambient conditions can be a significant problem in ceramic casting facilities, since kilns are used to fire the green ware. The intense heat generated by the firing process produces hotter, drier conditions in areas closest to the kiln, while areas away from the kiln and areas with outside ventilation have cooler, moister casting conditions.

Casting remains more an art than a science. Analytical models exist that explain interactions among small subsets of the process variables, however there are no analytical models that capture the dynamics of the entire casting process. Recently, artificial intelligence techniques have been used to model process behavior in areas where analytical models are unavailable. Dinger[2] developed an expert system to examine the effects of particle size distribution on slip rheology. Martinez, Smith, and Bidanda[3] used a neural network to predict cast quality, and Coit and Smith[4] developed neural network models for the casting rate and the moisture gradient.

2.2 Fuzzy Logic

The concept of the fuzzy set was first introduced by Zadeh[5] in 1965. In Boolean logic, an element either has full membership in a set or is not a member of the set at all. That is, it either has a degree of membership of 1 or 0. Fuzzy logic allows an element to have a degree of membership in a set which can take on any value between 0 and 1. If-then rule bases can then be developed that reason with these fuzzy sets.

The advantages of using fuzzy logic for process modeling include the ability to work with imprecise and noisy data, the ability to incorporate operator expertise directly into the modeling process, and the ability to easily work with qualitative data. In many situations, fuzzy logic systems have been successful in modeling systems where more traditional techniques have failed.

Examples of successful fuzzy logic applications in manufacturing include the development of a model to predict the running time of a steam cracking process.[6] Matshushita developed a washing machine that uses fuzzy logic to select machine settings such as length of wash, rinse, and spin cycles, water temperature, and others based on an examination of the laundry itself (dirt level, size of load, etc.).[7] King and Marsolan[8] used fuzzy logic to model time-variant dynamic changes in a thermal process unit.

3. Development of the Process Model

A fuzzy logic model was developed in conjunction with a major producer of sanitary ware in order to predict casting time for their slip-casting process. Figure 1 shows the structure of the model. Ambient temperature (°F), ambient humidity (%), and the age of the mold in weeks are presented as crisp, continuous inputs to a fuzzy rule base that predicts mold condition. Note that the mold age is uniform for the molds within an individual casting line. Mold condition is rated on an ordinal scale of zero to ten, with zero being the driest and ten being the wettest. This prediction of mold condition is then paired with a crisp, continuous prediction of the casting rate from a neural network model in order to predict the casting time in minutes through the use of a second fuzzy rule base. The casting rate is predicted by a neural network based on the physical properties of the slip including viscosity measures and other factors such as the proportion of sulfates present in the slip. The use of a neural network model for the casting rate reduces the reliance on test casts in determining casting time.

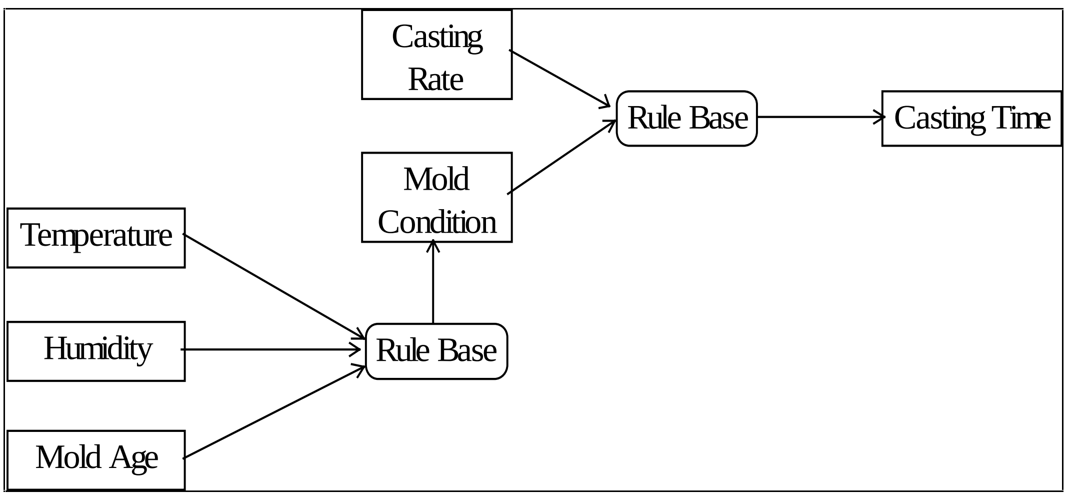

Figure 1 - Structure of the Casting Time Model

3.1 Development of the Membership Functions

A membership function for a variable shows the degree of membership in each of the variable's fuzzy sets for each value in the range of interest. For example, figure 2 shows that an ambient temperature of ninety degrees has a degree of membership of 0.33 in the fuzzy set "Low", a degree of membership of 0.5 in the fuzzy set "Medium", and a degree of membership of 0 in the fuzzy set "High". The membership functions for the ambient temperature, ambient humidity, and casting rate were developed through examining the frequency distributions from approximately two years of historical plant data. Each of these membership functions was developed using three fuzzy sets each in order to facilitate the rule elicitation process. The membership functions for mold age, mold condition, and casting time were developed in conjunction with the plant's ceramic engineers since little data is kept on these variables. Mold age was modeled using three fuzzy sets for elicitation purposes. The number of fuzzy sets for mold condition and casting time were set by the ceramic engineers in order to incorporate the full range of process dynamics. Ranges for each of the variables were set based on an examination of historical plant data.

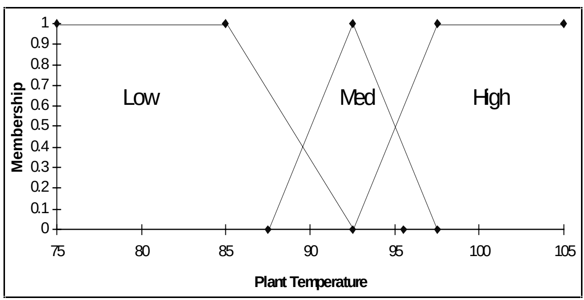

Figure 2 - Membership Function for Ambient Temperature

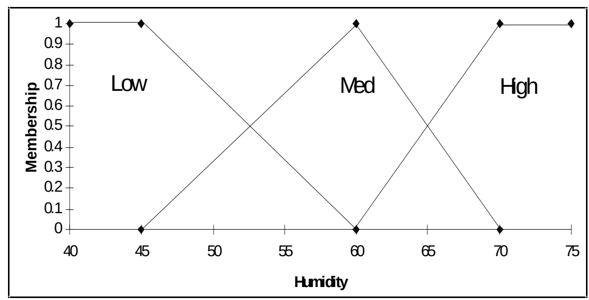

Figure 3 - Membership Function for Ambient Humidity

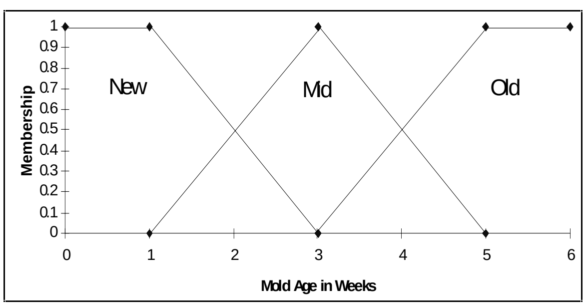

Figure 4 - Membership Function for Mold Age

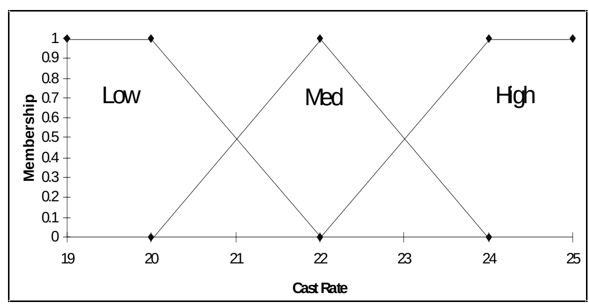

Figure 5 - Membership Function for Casting Rate

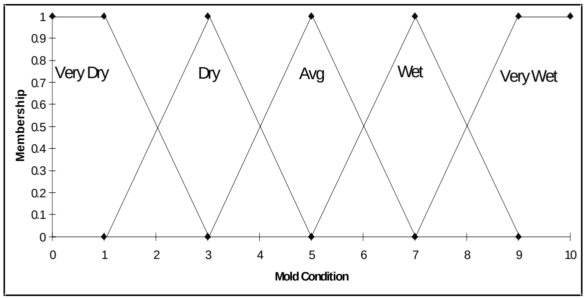

Figure 6 - Membership Function for Mold Condition

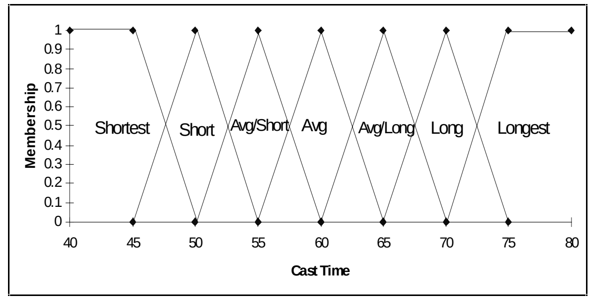

Figure 7 - Membership Function for Casting Time

3.2 Development of the Rule Bases

The fuzzy rule bases for both the mold condition and the casting time were developed by soliciting the expert knowledge of the plant's ceramic engineers. Three ceramic engineers were each asked to develop rule bases for both mold condition and casting time. 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. The three updated rule bases were then consolidated into a single rule base. Tables 1 and 2 below show the fuzzy associative memories (FAM's) for each rule base. A FAM is essentially a lookup table that shows the output value for each combination of inputs. For example, table 1 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*.

	Humidity / Age								
	Low			Medium			High		
Temperature	New	Mid	Old	New	Mid	Old	New	Mid	Old
Low	VDry	Dry	Avg	Dry	Avg	Wet	Avg	Wet	VWet
Medium	VDry	VDry	Dry	VDry	Dry	Avg	Dry	Avg	Wet
High	VDry	Dry	Avg	VDry	Dry	Avg	Avg	Wet	VWet

Table 1 - FAM for Mold Condition

	Mold Condition				
Cast Rate	Very Dry	Dry	Average	Wet	Very Wet
Low	AvgShort	AvgShort	Short	Longest	Longest
Medium	Short	AvgShort	Avg	AvgLong	Long
High	Shortest	Shortest	Short	Avg	AvgLong

Table 2 - FAM for Casting Time

3.3 Decision Support

The use of a predictive model for the casting time allows the ceramic engineers and foremen to set the casting time for individual benches or casting lines based on the temperature and humidity in that area of the plant, the age of the caster's molds, and the physical properties of the slip. This system has been installed at the sanitary ware facility for which it was developed, and it is currently being validated by the company's ceramic engineers.

Figure 8 shows a control surface for the mold condition rule base. The x-axis is the ambient temperature, the y-axis is the ambient humidity, and the z-axis shows the resulting mold condition prediction. For this control surface, the mold age was kept at a constant value of three weeks. Figure 9 shows the control surface for the casting time rule base. Here the x-axis is the casting rate, the y-axis is the mold condition, and the z-axis is the prediction of the casting time. Note that the control surfaces are clearly nonlinear yet have smooth transitions between control states.

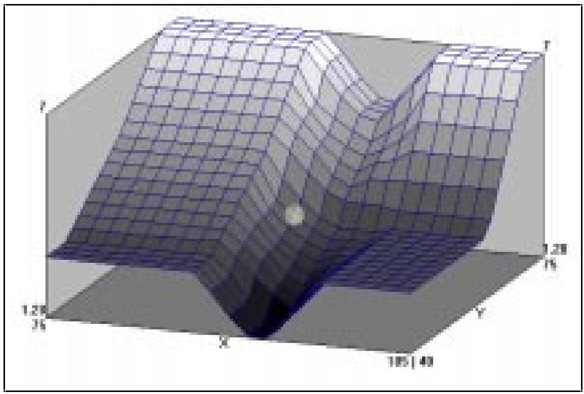

Figure 8 - Control Surface for Mold Condition Rule Base

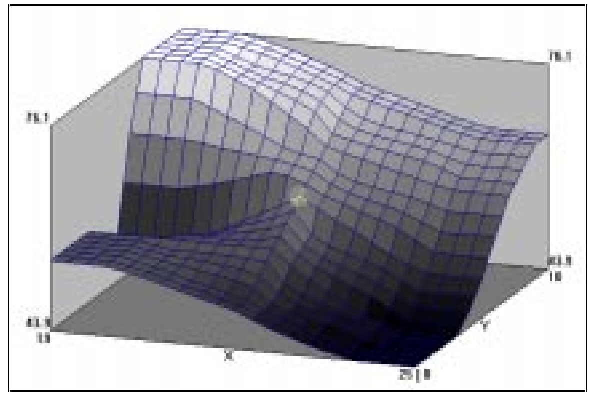

Figure 9 - Control Surface for Casting Time Rule Base

3.4 System Platform

The fuzzy logic rule bases were developed using Togai Infralogic's TILShell software package, version 3.0.1. The system was then compiled into a DOS executable file using the package's C code generation capabilities. This allows the system to be run on low-level PC's and in non-Windows platforms. This model was developed as a module for use within an integrated predictive quality control system for ceramic casting. Other modules within the system include nonlinear predictive models for the casting rate and moisture gradient of the slip-casting process, a design for control module that will recommend settings for controllable variables in order to produce a slip with a desirable casting rate and moisture gradient, a training module that presents case studies as a learning tool for newly hired ceramic engineers and foremen, and a data repository that records, summarizes, and charts plant data.

4. Conclusions

Fuzzy logic has been shown to be an effective technique for modeling casting time in the ceramic slip-casting process. Prior to the development of this model, there was no substitute for the knowledgeable assessment of an experienced ceramic engineer. Utilization of the system will allow casting time decisions to be made expediently, expertly, and consistently without the need for laboratory test casts or judgmental speculation. In addition, casting time decisions can be tailored to the casting conditions at specific benches, thereby controlling for the inherent variability in ambient conditions found in most ceramic ware manufacturing facilities.

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