Application of Intelligent Techniques for Controlling the Green Sand Properties

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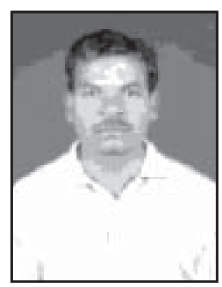

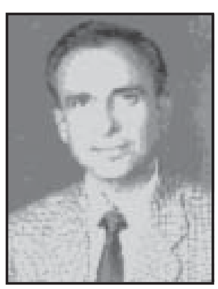

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ABSTRACT

In the present work an Artificial Neural Network model and a Neuro-Fuzzy model were developed for predicting the properties of clay bonded moulding sand mix. Experiments have been conducted to generate the data for modelling. Various sand mixes have been prepared varying the amounts of clay, coal dust, moisture and mulling time. For each sand mix composition, the permeability was measured. The models were trained and tested with data set and were used for predicting the properties of moulding sand mixture. The predicted values of the moulding properties obtained by the two models were found to be in good agreement with the experimental values. The results of the neuro-fuzzy model were compared with the results obtained from the neural network model. It has been observed that neuro-fuzzy model predicts the properties more accurately as compared to neural network model.

Individual foundries may generate their own green sand property data using their own raw materials and predict the properties for different sand compositions using such intelligent techniques.

***Keywords**:* Clay bonded sand, moulding properties, permeability, ANN Model, Neuro- Fuzzy model.

INTRODUCTION

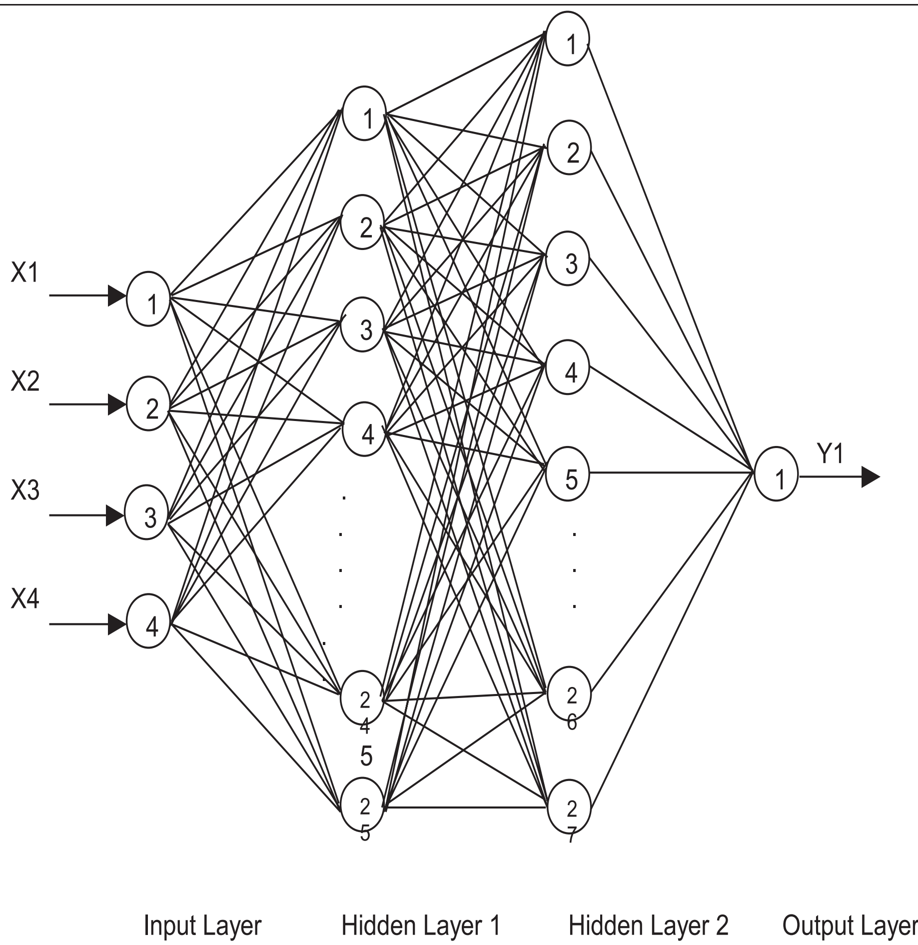
Substantial global iron casting tonnage is production, more emphasis has been given on quality besides its cost. The quality of castings depends to a large extent on the technology of mould making and characteristics of moulding materials. According to the production data on an average 40-70 percent of casting defects arises due to improper mould properties. Thus, it is imperative for the foundrymen to have the accurate selection of the moulding sand composition to get the desired properties.

Over the past several years, sand control has been practiced through the development of different laboratory tests, control graphs and computer programmes. With the development of high pressure moulding, the above mentioned sand control techniques could not be able to meet the present day requirements. Therefore, there began a quest for the development of new techniques for effective sand control. In view of these observations, artificial intelligent techniques seem to be quite useful tool for controlling sand. Till date, a few researchers [1,2] have applied intelligent techniques for green sand control and optimum formulation of the sand mix composition. In the present investigation an attempt has been made to develop artificial intelligent techniques for modelling the properties of clay bonded moulding sand mix, presently permeability.

Artificial Intelligence techni- ques such as neural networks and Fuzzy models have been studied in the recent years in the hope of achieving human like performance in the fields of engineering. Neural networks are highly effective tools, which can recognize similar patterns with generalization by training a network with a particular pattern of data. Their parallelism, trainability and speed make the neural networks fault tolerant as well as fast and efficient for handling large amounts of data [3]. Where as Fuzzy based systems emulates human behaviour in managing and solving problems that cannot entirely be formalized by the use of mathematical models and treated by the use of system theory approaches, fuzzy models require experts and decision makers who are well conversant with the process states and the input/output relationships to generate the linguistic rules[4]. All the rules are activated to a certain degree and produce output accordingly. The possible number of linguistic rules increases exponentially when the number of input variables increases. For some large complex systems, it is almost impossible to establish such a relationship model due to large amount of prepositions and the highly complicated multi dimensional fuzzy relationships and there exits a trade-off between precision and generalization requirements for the fuzzy models [5]. This can be effectively managed by neuro-fuzzy systems.

Neuro-Fuzzy systems which combine elements of both neural networks and fuzzy methodology, work in a similar way to back-propagation neural network systems. In neural networks the model is not defined a priori but obtained through a process of data training. The network progressively builds the input/output function by presenting couples of input and output data. For every input value introduced, the network calculates the output value and the corresponding value from the expected value. The learning algorithm thus modifies weight between neurons until the total error is minimized. In the neuro-fuzzy systems, the learning algorithm modifies the analytical expressions of the membership functions, so as to diminish the total error. In these systems practical heuristic approaches are designed and engineered. Like fuzzy system, experts do not require to generate the rules for a fuzzy neural network model, the model can automatically set up fuzzy variables and their membership functions as well as fuzzy rules with the numerical data collected from the past operations, thus avoiding the delicate and expensive codification phase.

In fact, neural networks and fuzzy logic can be considered as two complementary techniques. Neural network can learn from data and feed back in which the internal structures are difficult to understand and also they get inflexible once the network is established. In contrast, fuzzy rule based models are easy to comprehend because of their linguistic terms and the structure of the if-then rule base. Neuro-Fuzzy systems combine elements of neural networks and fuzzy methodology to gain the advantages of both the systems.



Network Architecture

X1 = Clay Content
X2 = Moisture Content
X3 = Coal Dust
X4 = Mulling Time
Y1=Green Compressive Strength

Number of hidden layers = 2
Number of neurons in hidden layer 1= 25
Number of neurons in hidden layer2 = 27
Number of training iterations = 31000
Learning Rate = 0.7
Momentum Factor = 0.8

Fig. 1 : *Four Layer back-propagation network architecture.*

In the present work, an attempt has been made to develop a Neural Network model and an ANFIS-type (Adaptive Neuro-Fuzzy Inference system) neuro-fuzzy system to predict the permeability behaviour of the clay bonded moulding sand mixture and to analyse the sand-mix composition. Further the results obtained from the neuro-fuzzy model are compared with the neural network model.

Significance of permeability in green sand Moulding

Sand moulds evolve volatile gases when filled with molten metal. Thus sufficient permeability is necessary to prevent the gases from developing high pressures and blowing into and through the metal. Permeability is the venting quality with which the sand permits free escape of gases through its pores between sand grains. Permeability therefore depends on the number and size of the pores, or on their number and total volume. The volume of pores in a granular material depends on the size, distribution of the grains and on the way in which they are packed.

In addition to base sand, permeability also depends on the additives made to the sand mix, binder, water additions, mulling time and the bulk density of the sand mix. When water and clay content of sand increases density increases. Higher the density, lower is the permeability. Good mulling increases permeability, which should be as high as necessary, not as high as possible.

Experimental Details

In order to develop artificial intelligent models to predict the Permeability of moulding sand mix, it requires sample data sets for training, testing and validation By considering the features of green sand moulding process, the amounts of clay, water, coal dust and mulling time were chosen as the input process parameters, while permeability was chosen as the output parameter for modelling. Standard experi-mental procedures have been followed to generate data for modelling. 142 sets of data were generated by varying the amounts of clay, water, coal dust and mulling time. For each sand composition the permeability was measured. The specified ranges of input parameters for experiments were selected based on the past investi-gations [6-11] and industrial practices.

Out of the total data generated from the experiments, 16 sets of data were selected randomly for testing the developed model and another 14 sets of data for validation of the developed network model. The remaining data of 112 sets were used for training the proposed network model.

Development of Neural Network Model

The learning algorithm selected for training the network is back-propagation algorithm. A C++ source code was compiled for developing the Back Propagation Neural Network (BPNN) model. The developed network was trained until the desired error limit of 0.001 set by the authors was reached. The connection weights for mini-mum error at the end of training were stored in a text file and were subsequently used for the prediction of permeability. After successful training the network, the architecture of the network obtained can be seen in Fig. 1.

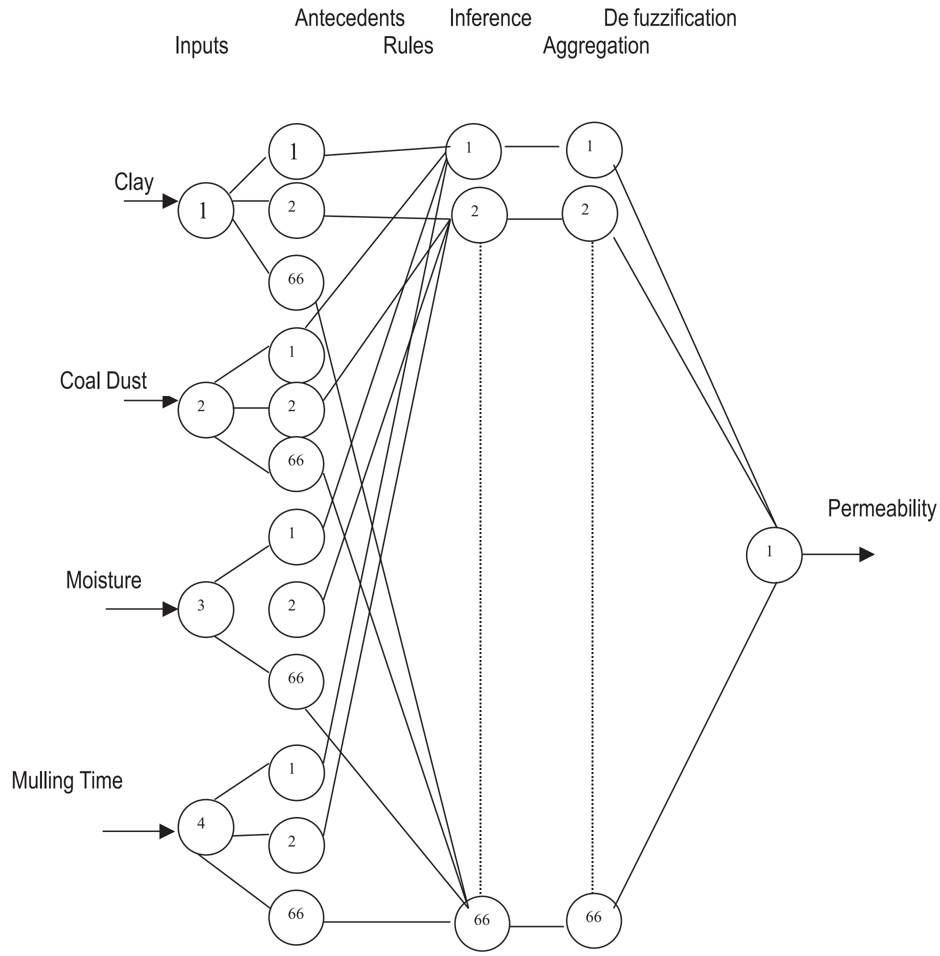


Fig. 2 : *Structure Neurons and Layers of a Neuro-Fuzzy System.*

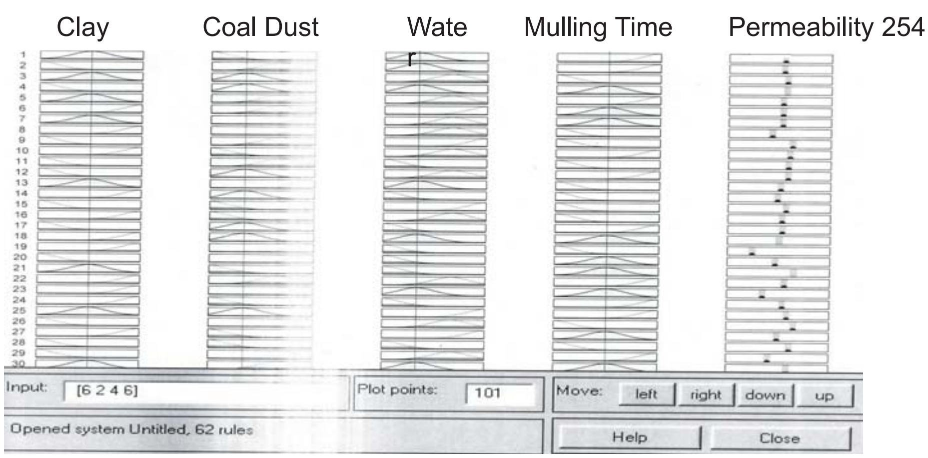


Fig. 3 : *Rule Viewer of the developed Neuro-Fuzzy Model.*

After the successful training of the network the performance of the network was tested with the test data sets. Sixteen different sets of data, which were not included in the training, were selected randomly as the test data set. The response of the network was accessed by comparing the predicted values of the network with those of the experimental values to determine the predictive capability of the network. The network can predict the best possible results when the input parameters selected are within the limits set earlier while experimental results are generated. The predictive (generalization) capability has been validated with a set of validation data which were not included in the training and test data.

Development of Neuro-Fuzzy Model

The same sample data sets that were used for back-propagation neural network model were used for the development of fuzzy neural network model. The input and output variables remain unchanged in regard to the neural network model. The designing and training the adaptive fuzzy model were performed using MATLAB 'Fuzzy Logic Toolbox, [12]. The learning algorithm that allows the system to learn dynamically from data is a combination of back-propagation and least square methods i.e. hybrid algorithm and the training stopping criterion was selected on the basis of error tolerance. When the training data is loaded, the adaptive fuzzy system automatically develops a Sugeno type Fuzzy Inference System (FIS) from input/output data for learning. In the learning process of the developed Neuro-Fuzzy model, all the membership functions of variables are assigned to

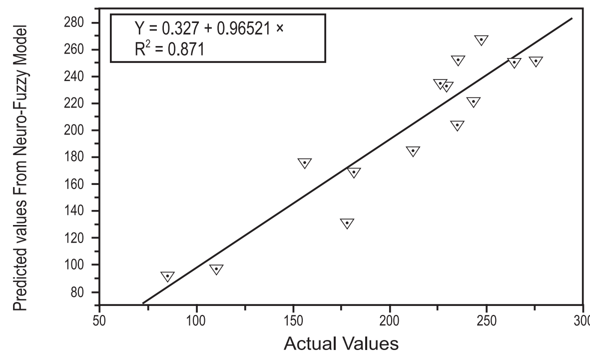


Fig. 4 : *Performance of the Neuro-Fuzzy System for the Simulation of Pemeability.*

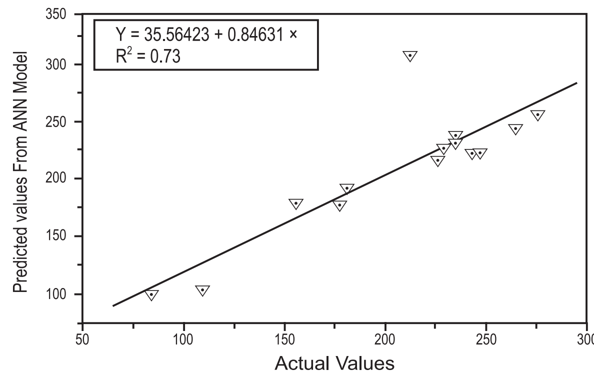


Fig. 5 : *Performance of the Neural Network Model for the Simulation of Permeability.*

Gaussian type membership function and the parameter subspaces were determined by using C-means clustering of the training set. The ANFIS generates 66 sets of fuzzy rules by the learning process. The learning rules control the generalization capability of the network. A schematic representation of the developed neuro-fuzzy model structure can be seen in Fig. 2. The fuzzy neural network model developed after training was tested against the test data and was further used to predict the permeability of moulding sand mixture.

ANFIS generates a rule viewer which is shown in Fig. 3, to predict the

Table 1 : *Comparison between the actual and predicted permeability of moulding sand mix*

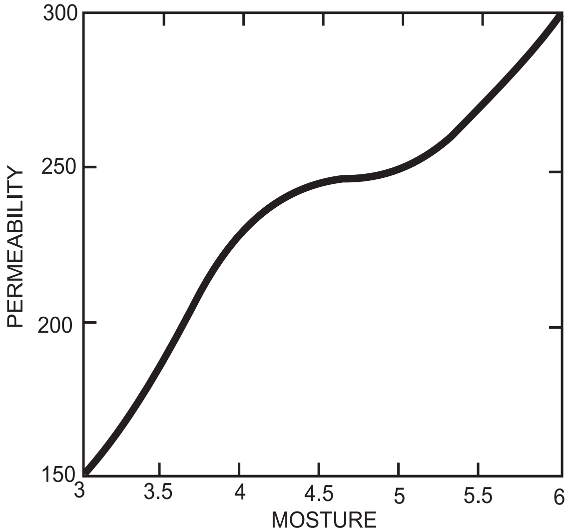
Sl. No	Clay %	Coaldust %	Moisture %	Mulling Time(Min)	Permeabllity				
					Actual	Predicted ANN	% Error	Predicted FNN	% Error
1	4	0	5	6	243	223.51	8.02	223	8.23
2	4	2	4	4	235	238.38	1.44	205	8.51
3	4	2	6	6	229	228.23	0.33	234	21
4	4	4	6	8	226	218	3.53	236	4.42
5	4	6	5	6	181.5	192.57	6.1	170	6.33
6	6	0	4	4	264	244.91	7.22	252	4.54
7	6	0	6	8	212	309.43	45.96	186	12.26
8	6	2	4	6	235	232.64	1	254	8.08
9	6	4	3	8	156	179.57	15.37	177	13.4
10	6	6	3	6	110	104.51	4.99	97.7	11.8
11	8	0	5	6	275	257.11	6.5	253	8
12	8	2	4	8	247	224.03	9.29	259	10.7
13	8	4	3	6	85	100.68	18.44	92.3	8.5
14	8	6	4	8	178	178.33	0.185	132	25.4

permeability number of green sand mixture. An effectively trained network with accurate data set can generate rule viewer which can accurately predict the permeability when the input variables selected are within the best possible ranges of input process parameters.

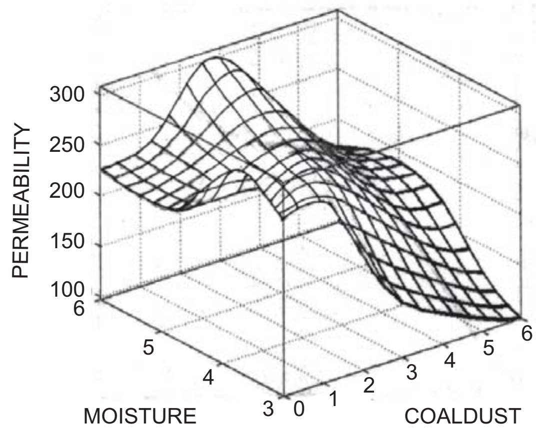
Results and Discussion

The predicted results of the neuro-fuzzy model were compared with the results of the back-propagation neural network model. Table 1 represents the comparison between the actual and predicted values of permeability of the moulding sand mix by the two developed models. The linear regression analysis has been carried out between the actual permeability and the predicted permeability to evaluate the performance of the developed network models by the two intelligent techniques. The coefficient of correlation (R^2) values obtained are 0.87 and 0.73 respect-ively which is shown in Fig. 4-5. It may be inferred from the Fig. that neuro-fuzzy model can predict the properties of moulding sand more accurately as compared to back-propagation neural network model because of high learning precision and generalization. It has also been observed during the training that the neuro-fuzzy model requires less learning time as compared to BPNN.

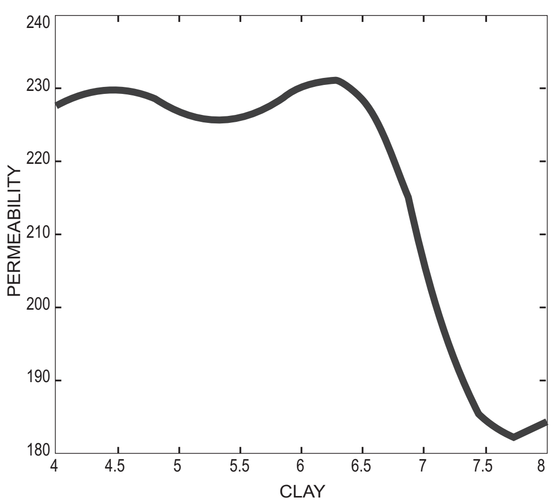
In addition to the accurate prediction, ANFIS can also be effectively used for analysing the sand mix composition for different processing parameters. ANFIS generates 2-D and 3-D graphs which exhibit the relationship between the input and output processing



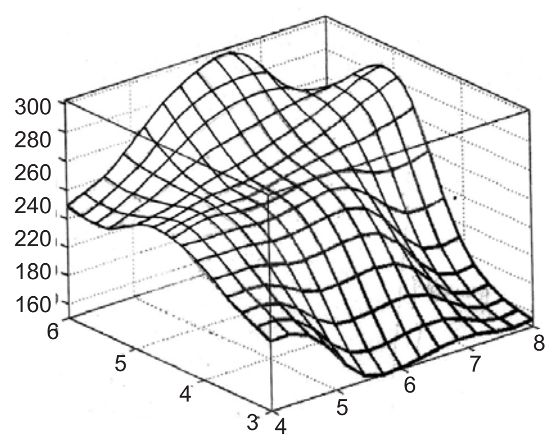
a. *For clay 4%, coal dust 3% and Mulling time 6 Minutes.*



c. *For clay 6% and Mulling time 4 Minutes.*



b. *For clay 4%, coal dust 3% and Mulling time 6 Minutes.*



d. *For clay 6% and Mulling time 4 Minutes.*

Fig. 6 : *Some Model Graphs developed by FNN Model.*

parameters. The 2-D graphs generated by the proposed neuro-fuzzy model depict the relationship individual input variable such as clay, coal dust, moisture and mulling time on permeability. The 3-D output surfaces are helpful in evaluating the combined affect of two input parameters on permeability by keeping the other variables as constant. Some of the model graphs generated by the Neuro-Fuzzy model are shown in the Fig. 6(a, b, c and d).

CONCLUSIONS

It is well known fact that artificial intelligent techniques reduce or eliminate the time consuming task of repetitive experimentation for finding the optimum parameters. Two most important conclusions that can be drawn from the present work are:

(i) Neuro-Fuzzy models have higher learning precision and generalization capability and can predict the permeability of clay bonded moulding sand mix more accurately than the back-propagation neural network model.

(ii) The application of neuro-fuzzy models can reduce the learning time by self adjusting the dynamic state learning parameters and can converge more rapidly.

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