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Investigation on the Role of Moisture Content, Clay and Environmental Conditions on Green Sand Mould Properties

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ABSTRACT

The quality of castings in a green sand mould is influenced significantly by its properties, such as green compression strength, permeability, mould hardness, and others, which depend on input parameters. The relationships of these properties with the input parameters, like sand grain size and shape, binder, water, clay, etc. are complex in nature.

The goal of this paper is to determine the green sand mould compressive strength in case of input parameters. For this, the author have used Neuro-Fuzzy modeling and Several experiments on green sand mould have been done for molding the Aluminum parts and have been used for training, validation and testing the model. The efficiency of the model then has been evaluated with the new experiments. The results show that by using Neuro-Fuzzy model we can estimate the compressive strength of green sand precisely (Error is about 10%) before molding.

KEYWORDS: Moisture, Clay, Environmental Conditions, Green Sand Compressive Strength, Neuro Fuzzy.

1. INTRODUCTION

Green sand molding is one of the oldest and most popular methods in world. The goal of the companies is to provide a part with acceptable quality and low cost. The molding mixture is composed of sand, adhesive, water, clay and so on. The compressive strength of sand which is the capability of sand for maintaining sand grains can be measured via compressive and shear tests. The compressive strength depends on shape, size and aggregation of sands and also water and other additives. The cause of most defects in this method relates to sand mixture. The role of moisture is more than others and the maximum strength and minimal defects in parts can be achieved by knowing the certain amounts of moisture and clay. More research on green sand moulds for improving its properties has been done in 1960-1970 and is both practical and theoretical aspects. The composition of the molding sand affects the mold properties and thus the quality of the finished casting. Designing the green sand parameters plays an important role in getting a quality casting. For many years, sand control had been practiced through evaluation of the physical properties of the sand mixtures in line with the recommendations made.

Some different methods for sand testing and also some control graphs have been created that are very useful [1].Y. chang and his colleagues investigated the relation between density and compressibility of sand. Their model was an experimental formula for predicting the compressive strength and density of the molding mixture according to the water content. They also developed a new model for studying the permeability of the sand and presented their experimental results to show that how the permeability is affected by moisture, bentonite and so on [2].The other researchers have investigated the effect of parameters such as betonies percentage and sand mulled time on sand properties by using statistical methods [3]. As regards achieving the optimum combination of sand mixture is one of the main problems in casting industries; in other studies the effect of grain size, amount and percentage of clay, moisture content and grain hardness in the shear strength and permeability of sand is investigated [4].In other research, the properties of sand are investigated by using neural network and neuro fuzzy models. In this study the penetration rates of the sand based on different amounts of clay, moisture and mulled time has been studied. The results obtained by neural networks and fuzzy models compared with practical experiments and are consistent with each other [5].In the other research, modeling the properties of sand is performed by using Back Propagation Neural Network (BPNN) and Genetic Algorithm (GA) [6].Also, other researchers have modeled the relation between input and output parameters of the sand using neural networks and genetic algorithms and shown that we can control the desired properties of sand by using Artificial Neural networks and genetic algorithm methods [7, 8].

In the present work, an attempt has been made to develop an ANFIS-type (Adaptive Neuro-Fuzzy Inference system) neuro-fuzzy system to predict the compressive strength of the clay bonded moulding sand mixture and to analyze the sand mix composition.

The scientific contributions of this paper are:

1) the prepared mixture of sand must take certain properties over time to produce quality pieces
2) predicting the compressive strength of sand before moulding

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3) decreasing the production cost and increasing the productivity

2. MATERIALS AND METHODS

Using a given input/output data set, the ANFIS method constructs a fuzzy inference system (FIS) whose membership function parameters are tuned using either a back propagation algorithm alone, or in combination with a least squares type of method. This allows fuzzy systems to learn from the data they are modeling. FIS Structure is a network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs [9].

According to the above explanations we can train the model by using data obtained from experimental tests and predict the compressive strength on the new input vectors of moisture content and clay at environmental conditions. Then the new input vectors that are not used in training stage apply to the model and the correct answer obtain from the model. So, some of the data as a test data are excluded to ensure the integrity and convergence of the model [10].

Considering that sand casting method is mostly used in factories and training sites, the prepared mixture of sand must take certain properties over time to produce quality pieces. Because the effect of moisture and clay on the quality of sand is more than others, several experiments with different moisture and clay contents in 4 different times and environmental conditions have done to obtain data required for compressive strength estimation. These data is used for training, validation and testing the model.

The Compressive Strength of casting sand is the maximum compressive stress that the standard sample can tolerate before it is affected by fragmentation. The sample is a cylinder with diameter and height of 50.8 millimeters which is made by using sand rammer shown in Figure 1. Molding sand mixture, which contains sand with number of AFS = 79.5 and 10% Bentonite and different moisture and clay content knocked three times and compressive strength of mixture in four stages (each time a load) is measured [11].

Figure1. The Sand rammer

To determine the compressive strength of the sand we have used the Universal Strength Machine-type (pfg)shown in Figure 2.The equipment is used to determine various strengths, such as compression, shear, tensile, transverse and deformation, of foundry sand. It consists of hydraulic unit, high and low pressure gauge, set of compression pads, compression range high up to 13 kg/cm^2, low up to 1600 gr/cm^2. The device has a part to place the sample along the length and centrally as shown in Figure 3.This section is composed of two jaws, one fixed and other moves with the lever and flat Jaws come together and apply force to the sample.

The Compressive force applies with rate of 25gr/cm^2 until the sample breaks into and after the defeat, the maximum tension that samples can tolerate are shown [11].

Figure2. Universal Strength Machine-type (pfg)

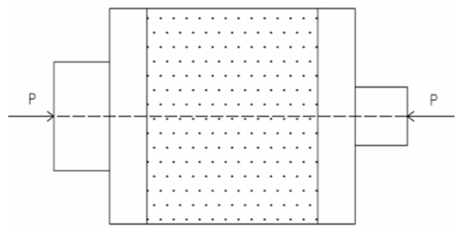

Figure3. The method of replacing the sample

To create an appropriate structure for the model and training it, several experimental tests were carried out and the results shown in table1.

Table1. The experimental results

First Day					
Humidity		43%	47%	49%	50%
Temperature		24˚C	24˚C	22˚C	21˚C
Moisture Content (%)	**Clay (%)**	**Compressive Strength (×100 gr/cm^2)**			
3	**4**	**2.85**	**3.15**	**2.55**	**3.40**
4	**5**	**4.90**	**4.80**	**4.65**	**4.75**
5	**5**	**5.40**	**5.70**	**5.30**	**6.00**
5.5	**5**	**5.70**	**5.85**	**5.90**	**6.30**
6	**6**	**6.45**	**6.50**	**6.50**	**7.00**
6.5	**6**	**6.60**	**6.85**	**6.50**	**7.10**
Second Day					
Humidity		49%	50%	49%	49%
Temperature		23˚C	23˚C	21˚C	21˚C
Moisture Content (%)	**Clay (%)**	**Compressive Strength (×100 gr/cm^2)**			
7	**6**	**5.80**	**5.40**	**5.50**	**5.00**
7.5	**7**	**5.70**	**5.60**	**5.80**	**5.30**
8	**6**	**6.00**	**5.60**	**5.85**	**5.47**
8.5	**7**	**5.78**	**5.79**	**5.38**	**5.60**
9	**8**	**5.46**	**5.35**	**5.70**	**5.35**
9.5	**8**	**5.30**	**5.45**	**5.67**	**5.80**
Third Day					
Humidity		49%	51%	50%	52%
Temperature		22˚C	21˚C	21˚C	20˚C
Moisture Content (%)	**Clay (%)**	**Compressive Strength (×100 gr/cm^2)**			
10	**9**	**2.85**	**3.27**	**3.40**	**2.85**
10.5	**9**	**2.75**	**2.30**	**2.33**	**2.58**
11	**9**	**2.81**	**2.45**	**2.31**	**2.54**
12	**10**	**2.30**	**2.26**	**2.35**	**2.31**
13	**10**	**2.11**	**2.20**	**2.24**	**2.28**
14	**11**	**2.05**	**2.10**	**2.05**	**2.15**

As indicated in Figure 4, the system has a total of five layers. The functioning of each layer is described as follows.

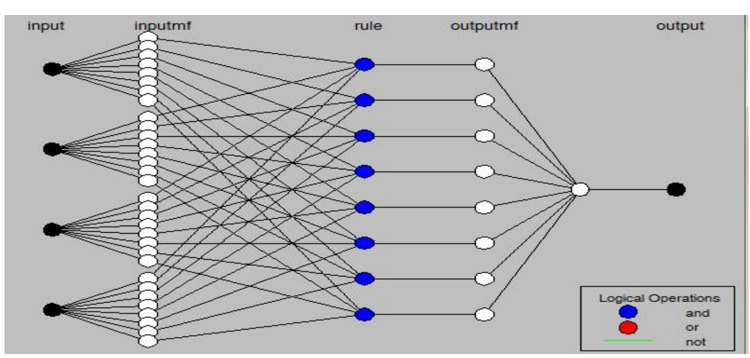

Figure4. Structure Neurons and Layers of a Neuro-Fuzzy System

In the first layer (fuzzification layer) the crisp inputs are fuzzified through membership functions. In this paper, all the membership functions are Gaussian functions. In second layer (rule layer), output of each node shows the firing strength of a rule that is generated by cross multiplying all of the membership function obtained from the first layer. In the third layer (normalization layer), each node calculates of the ratio of the i^{th} rule's firing strength to the sum of all rule's firing strengths as normalized firing strengths. The fourth layer (consequent layer) multiplies thenormalized firing strength with the linear consequence. The fifth layer (output layer) computes the overall output as the summation of all obtained values from layer 4 [12].

3. RESULTS AND DISCUSSION

For training the Network, data from practical tests inTable1 were used. The training data for network is a result of any experiment in which the input and output values are known. Figure 4 shows the training and validation errors in which the network is reached its best state at about 100 epochs.

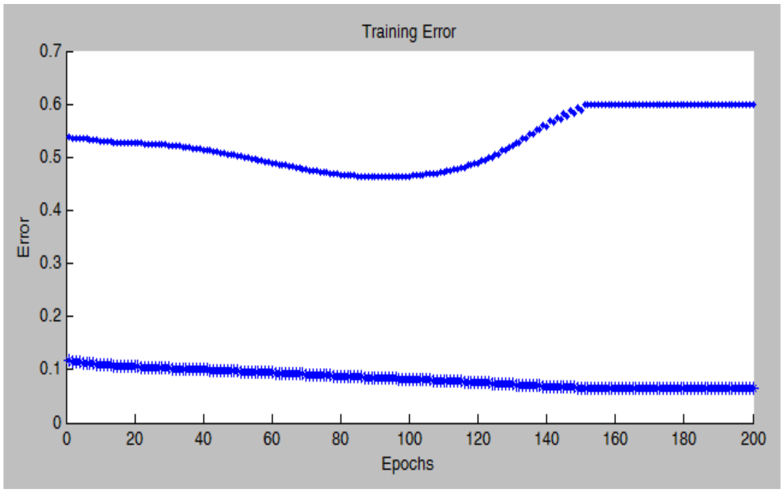

Figure 4. Training and validation error in neuro fuzzy models

After creating a model using data from different experiments conducted to determine the compressive strength on the sand, (Table 1), we tested the model with the amount of moisture and clay in different environmental conditions shown in table 2 and compared with the results obtained by the experimental tests. The results are shown in figures 5, 6. Theresults are in good agreement with each other.

Table2. The predicted compressive strength of sand for validating the model

Experiment No.	Humidity	Temperature	Moisture Content (%)	Clay (%)	Compressive strength (×100 gr/cm2)
1	43	24	5.5	5	5.67
2	47	24	5.5	5	5.86
3	49	22	5.5	5	5.69
4	50	21	5.5	5	6.33
5	49	22	11	9	2.44
6	51	21	11	9	1.8
7	50	21	11	9	2.15
8	52	20	11	9	2.46

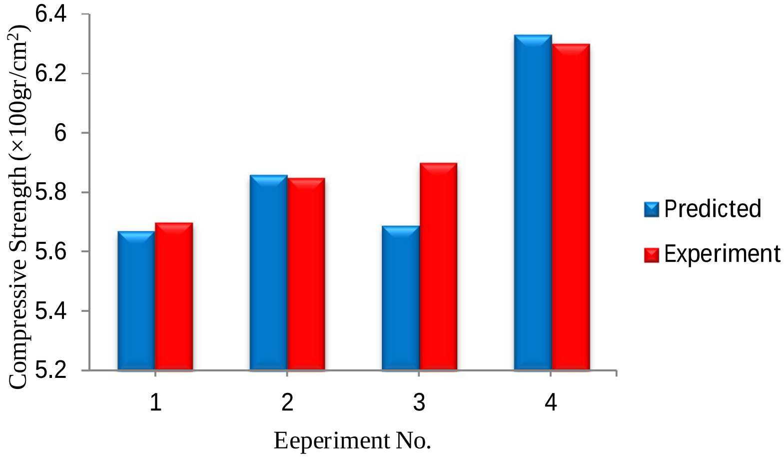

Figure5. The comparison between the experiment and predicted results in 5.5% moisture and 5% clay

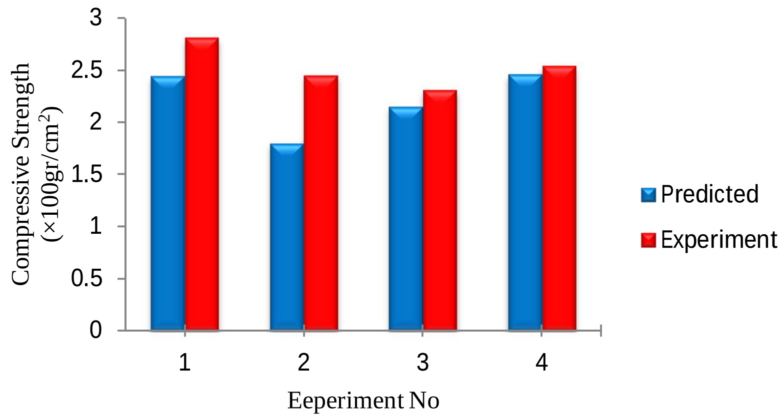

Figure6. The comparison between the experiment and predicted results in 11% moisture and 9% clay

Table 3shows the predicted ANFIS results and new experiments (compressive strength of sand) for testing model.

Table3. The experiments for testing the model

Humidity	Temperature	Moisture Content (%)	Clay (%)	Compressive strength (×100 gr/cm2) experimental	Compressive strength (×100 gr/cm2) predicted	Error %
45	22	6.2	7	3.20	3.37	5.044
46	24	6.2	7	3.95	4.30	8.139
46	23	6.2	7	3.59	3.41	5.278
47	24	6.2	7	3.67	3.42	7.309
45	22	9.2	8	1.80	1.61	11.801
46	24	9.2	8	1.64	1.44	13.888
46	23	9.2	8	1.95	2.22	12.162
47	24	9.2	8	2.10	1.85	13.513

Comparing the presented results in table 3 we get that the error in moisture content 9% and clay 8% is to some extent high. The reason is that the common moisture percent in casting of ferrous and nonferrous materials are different and for aluminum is about 6-8.5%, for steel is about 4-6% and for cast iron is about 6-8%. In the water content higher than these values because of the advent of new parameter "dehydration", the model loose its capability in predicting the precise outputs because the effect of dehydration is not investigated [13].The coefficient of correlation (R^2) value obtained is 0.9465 respectively which is shown in Figure7.

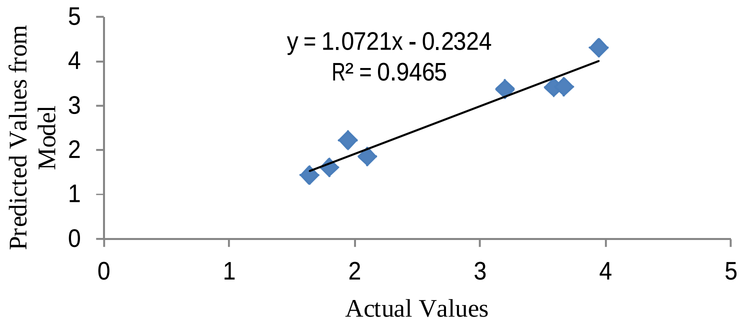

Figure 7. Performance of the Neuro-Fuzzy System for the Simulation of Compressive Strength

In addition to the accurate prediction, ANFIS can also be effectively used for analyzing the sand mix composition for different processing parameters. According to the widespread use of sand casting in the industry and the importance of producing high quality parts in this method, which is influenced by the strength of the mold and to the other hand the amount of moisture and clay in the sand, using the results of this study, we could prevent scraps in production line after a few hours stop that will reduce costs and increase production efficiency.

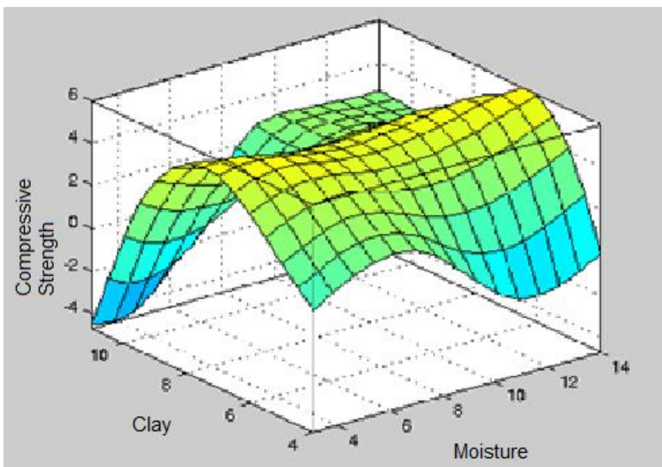

Figure 8 shows the 3-D output surface which is helpful in evaluating the combined effect of two input parameters on compressive strength by keeping the other variables as constant. It shows compressive strength of sand as a function of two inputs clay and moisture percent. Considering the surface we can analyze the proper amount of moisture and clay when preparing the sand mix for moulding.

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