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# MODELLING OF PROCESS PARAMETERS OF SILICATE BONDED CO2 MOULD MADE OF RECLAIMED CO2 SAND USING ARTIFICIAL NEURAL NETWORKS

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## ABSTRACT

*$CO_2$ moulding process due to its ability to produce harder moulds is widely used for casting variety of metals and especially high density alloys like steels, but due to the inherent drawback of $CO_2$ sand moulds i.e., poor collapsibility, the subject of reclamation of CO2 moulding sand has gained enormous importance. It is required to maintain stringent control over the process parameters of the $CO_2$ sand moulds made of reclaimed $CO_2$ sands, to yield the best possible quality moulds. There is a need to build up an intelligent system that can predict the properties of the mould with a practically reasonable accuracy. In the present investigation it is attempted to model process parameters of $CO_2$ moulding process using reclaimed $CO_2$ sand. Input parameters considered are % of sodium silicate, gassing time ,mixing time,% of coal dust and output parameters are mould hardness, permeability ,Compression strength, Collapsibility and tensile strength. Configurations of the developed ANN Models for $CO_2$ mould made of Reclaimed $CO_2$ sand is 4-48-38-5 with a learning rate of 0.8 and a momentum rate of 0.8 Developed ANN model shows good match with experimental results.*

***Keywords:*** *$CO_2$ moulding, sand moulds, reclaimed*

## 1. INTRODUCTION

In some fields such as Foundry, Welding and Metal Working the useful range of independent variables is rather narrow. To conduct experiments at a number of predetermined levels within the narrow range poses difficulties [1]. Further modification of statistical models by incorporating new random data is not possible. These limitations can be addressed effectively with the artificial neural networks.

### 1.1 Importance of Moulding Sand Reclamation

Major concern for every foundry unit is processing the required quantity of sand to impose the required characteristic on it to yield the castings of sound quality. Dwindling natural resources, increase in transportation cost due to galloping fuel price and environmental concerns made attention of foundry men focused on sand reclamation.CO2 moulding process is pushed aback due to evolution of organic binders but environmental concerns again brought the process in to fore front .$CO_2$ moulding process, due to its ability to produce harder moulds is widely used for casting variety of metals and alloys and especially high density alloys like steels. Advantage of $CO_2$ process is superior mould hardness but suffering with drawback of poor collapsibility. Hence breaking the lumps of knockout $CO_2$ sand and their reclamation is to be considered carefully. There are basically three methods of foundry sand reclamation i) Wet reclamation ii) Thermal reclamation iii) Dry reclamation .Through review of the literature on "Foundry sand reclamation "[3, 4], it is concluded that dry reclamation is the appropriate choice for reclaiming silicate bonded sands.

**1.2 Relevance of Application Artificial Neural Network to the Current Problem:**

It is required to control the process parameters of the $CO_2$ sand moulds to yield the best possible quality moulds. In some cases, depending on the nature of alloy being cast, either permeability may be important or mould hardness and compression strength may be important or lower collapsibility strength may be important. To control these properties a stringent control is to be exercised over the process parameters of $CO_2$ moulding. In many instances it is difficult to perceive the trend of change of mould properties with respect to change in the process parameter values. Although the previous investigations were helpful in identifying the variable factors, the optimum formulation of sand mixture remains critical problem for foundry men. Hence there is a need to build an intelligent system that can predict, with the help of a given set of input parameters, the properties of the mould with a practically reasonable accuracy. Application of artificial intelligence is well demonstrated in the fields of electronics and computer science. In rare cases it is also applied to problems of production engineering. In the present work it is attempted to model the process parameters of $CO_2$ mould with reclaimed $CO_2$ sand using Artificial Neural Networks (ANN).ANN based on the concept of synaptic weights and neurons have been able to recognize complex relationship between variables that would be difficult to recognize with traditional modeling technique [5].Neural networks excel in controlling difficult process. These are best suited when the system that needs to be controlled has some of the following characteristics [5].

i) Noisy data
ii) Non-linear relation between input and output parameters
iii) Multivariate (multiple inputs and outputs)
iv) System cannot be adequately modeled with traditional methods v) effect of all inputs is not completely understood. Silicate bonded $CO_2$ moulding process meets many of the afore mentioned characteristics and hence it is attempted to model the properties of the $CO_2$ mould Made of reclaimed $CO_2$ sand through Artificial Neural networks.

## 2. OBJECTIVE

To develop an intelligent Artificial Neural network model that can predict the properties of $CO_2$gas cured silicate bonded sand moulds made of reclaimed $CO_2$sands. Important input parameters fed to the Artificial Neural Network model are percentage of sodium silicate, quantity of $CO_2$gas (gassing time), mixing time, and percentage of coal dust. Outputs expected from Artificial Neural Network are Mould Hardness, Permeability, Compression Strength, Collapsibility and Tensile Strength.

## 3. METHODOLOGY

i) Obtaining the experimental data with a well-planned experimental design.
ii) Normalisation of data
iii) Fixing of number of hidden layers between input and output layer, number of nodes in each respective hidden layer. Adequate training of the network using BPNN.

### 3.1 Obtaining the Experimental Data:

As much experimental data as possible about the process parameters and the concerned mould properties is to be obtained .The utility of the neural network depends on the accuracy with which the experiments are conducted. Standard sand specimens of size 2" x2" are prepared using the sand rammer. Experimental setup utilizing rotameter is developed for gassing the specimen accurately. Experiments are designed such that as far as possible the true situation of variation of mould properties with respect to the process parameters is brought out. This enables the neural network to understand and analyze the data properly and in turn appropriate answer, within the tolerable error band, to any query that is imposed to the developed network during testing .Percentage of sodium is varied between 3 to 7 and the percentage of coal dust is varied between 0 to 2 and the amount of gassing time is varied between 8 to 30 seconds (quantity of $CO_2$ gas is appropriately converted in to gassing time) and mixing time is varied between 5 to 10 minutes. The input parameters for each experimental trail combination and corresponding results are given in Table 1.

Table 1: Details of input parameters of various experimental trail combinations conducted and their results to model $CO_2$ mould made of Reclaimed sands.

| Trail No | Sodium Silicate | Coal dust | Mixing Time | Gassing time | Mould hardness No | Permeability No | Compression Strength | Collapsibility | Tensile Strength |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 3 | 0 | 5 | 8 | 28 | 900 | 0.12 | 0.12 | 0 |
| 2 | 3 | 1 | 6 | 13 | 61 | 418.33 | 1.11 | 0.76 | 0 |
| 3 | 3 | 2 | 7 | 20 | 59 | 248.66 | 1.1 | 0.4 | 0 |
| 4 | 3 | 0 | 8 | 22 | 40.33 | 460.33 | 0.64 | 0.84 | 0 |
| 5 | 3 | 2 | 10 | 28 | 55.5 | 301.66 | 2.45 | 0.43 | 0 |
| 6 | 3 | 0 | 5 | 26 | 44.33 | 683.33 | 0.52 | 0.87 | 0 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 7 | 3 | 2 | 10 | 30 | 56 | 232.66 | 2.98 | 0.46 | 0.2 |
| 8 | 4 | 0 | 5 | 8 | 49 | 810.33 | 1.96 | 1.69 | 0.2 |
| 9 | 4 | 2 | 7 | 20 | 62 | 462.5 | 2.39 | 1.02 | 0.35 |
| 10 | 4 | 1 | 10 | 28 | 71.33 | 370.33 | 7.56 | 3.26 | 0.76 |
| 11 | 4 | 2 | 5 | 26 | 59.5 | 521.33 | 2.08 | 0.48 | 0.63 |
| 12 | 5 | 0 | 5 | 8 | 54.66 | 505.66 | 3.18 | 2.51 | 0.51 |
| 13 | 5 | 1 | 6 | 13 | 68 | 275.66 | 4 | 1.96 | 0.68 |
| 14 | 5 | 2 | 7 | 20 | 61 | 344.33 | 2.84 | 1.07 | 0.61 |
| 15 | 5 | 1 | 10 | 28 | 73 | 340.66 | 4.69 | 3.64 | 0.8 |
| 16 | 5 | 2 | 5 | 26 | 70.3 | 380.66 | 4.41 | 3.53 | 1.43 |
| 17 | 5 | 0 | 7 | 28 | 65 | 362.33 | 4.98 | 8.86 | 0.76 |
| 18 | 6 | 0 | 5 | 8 | 68.33 | 263.5 | 4.03 | 4.32 | 0.69 |
| 19 | 6 | 1 | 6 | 13 | 78 | 266.33 | 4.48 | 4.09 | 1.47 |
| 20 | 6 | 2 | 7 | 20 | 77 | 275.33 | 4.72 | 3.97 | 0.84 |
| 21 | 6 | 0 | 8 | 22 | 80 | 289.66 | 5.16 | 4.16 | 1.31 |
| 22 | 6 | 1 | 10 | 28 | 85.33 | 302.5 | 7.04 | 6.38 | 1.4 |
| 23 | 6 | 2 | 5 | 26 | 80 | 640.66 | 6.13 | 2.96 | 1.32 |
| 24 | 6 | 0 | 7 | 28 | 82 | 590.43 | 7.36 | 8.18 | 0.9 |
| 25 | 7 | 2 | 7 | 20 | 80 | 238.5 | 0.08 | 4.29 | 0.3 |
| 26 | 7 | 1 | 10 | 28 | 21 | 192.33 | 0.36 | 0.2 | 0.32 |
| 27 | 4 | 0 | 5 | 13 | 68.33 | 630 | 4.04 | 1.86 | 0.76 |
| 28 | 4 | 2 | 10 | 13 | 58.33 | 595 | 3.84 | 1.88 | 0.98 |
| 29 | 4 | 2 | 5 | 30 | 67.33 | 550.66 | 3.98 | 0.38 | 1.01 |
| 30 | 4 | 0 | 10 | 30 | 67.33 | 780 | 3.2 | 2.94 | 0.91 |
| 31 | 6 | 2 | 5 | 13 | 82.33 | 110.66 | 5.46 | 3.18 | 1.29 |
| 32 | 6 | 0 | 10 | 13 | 74.66 | 301.6 | 4.83 | 5.87 | 1.04 |
| 33 | 6 | 0 | 5 | 30 | 81 | 233.66 | 5.38 | 5.06 | 1.18 |
| 34 | 5 | 0 | 10 | 22 | 69.66 | 225.5 | 1.89 | 8.47 | 1.2 |
| 35 | 5 | 1 | 5 | 30 | 76 | 245.5 | 4.68 | 3.96 | 0.86 |
| 36 | 6 | 2 | 5 | 22 | 70.5 | 321 | 2.61 | 1.59 | 0.99 |
| 37 | 6 | 0 | 7 | 30 | 77.33 | 326 | 4.72 | 9.26 | 1.2 |
| 38 | 6 | 2 | 10 | 30 | 74.66 | 243.66 | 5.17 | 2.65 | 1.33 |

### 3.2 Data Normalisation:

The input and output parameter values fed to the neural network shall be normalised. Neural network can work with the data in the range of (0,1) or (-1,-1).The data is normalised using the following equation[8]

$$V^{1} = \frac{v - \min A}{\max A - \min A}(\text{new\_max } A - \text{new\_min } A) + \text{new\_min } A \qquad (1)$$

Where max A=the maximum value of the property considered (either mould hardness, permeability etc); min A=the minimum value of the property considered (either mould hardness, permeability etc); V=Exact value of the property experimentally determined using the specified input variable as mentioned in the experimental design; V=Normalised value of the property: New_ max A=1; New _ min A=0

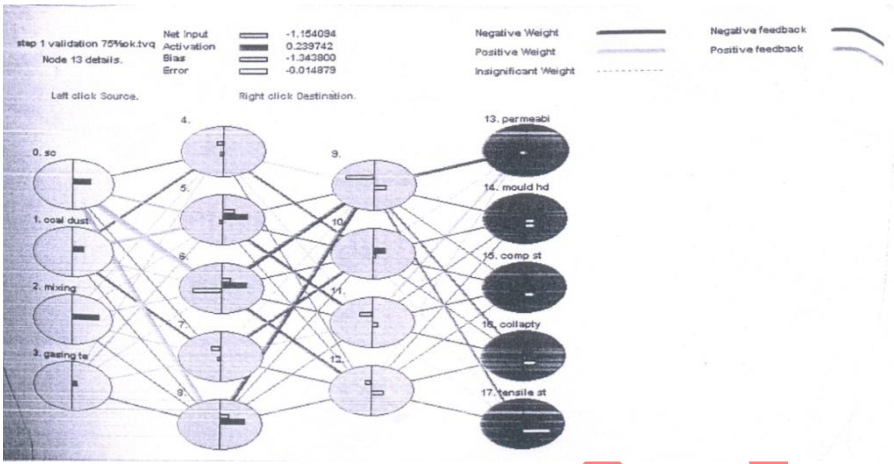

Fig .1 Network **architecture (Representative figure)**

### 3.3 Fixing the Network Architecture and Training

Out of the whole experimental data few of the data is randomly chosen for the purpose of validation. Back propagation learning algorithm, due to its wide acceptability [9] is employed to train and validate the data set for the current problem. BPNN utilizes sigmoid function for continuous updating of weights. By varying the number of hidden layers and the number of neurons in each hidden layer, initialized weight values, learning rate and momentum rate the appropriate network architecture is decided. The representative fig of the developed ANN is given in Fig-1.Graph showing the mean squared error versus learning cycles is given in fig -2. Training and validation graph is given in Fig-3

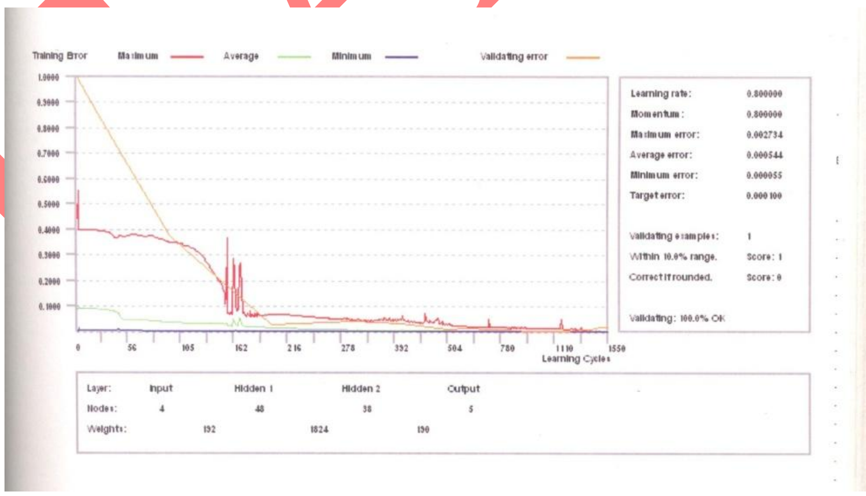

Fig 2 Graph showing the mean squared error vs. learning cycles

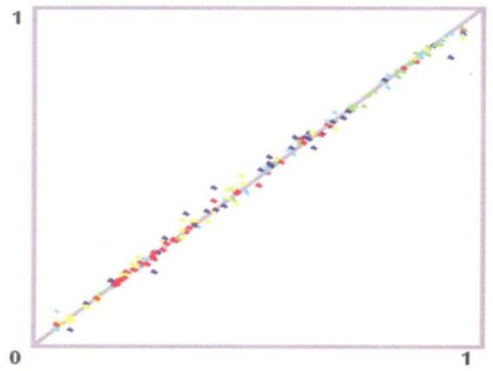


Fig .3 Training and validation graphs

### 3.4 Testing of the developed ANN:

Predictions are made from the developed ANN and the same is compared with the experimentally obtained data and the error percentages with respect to the experimental values are shown in Table 2.

**Table 2. Testing of ANN model developed for $CO_2$ mould made of reclaimed CO2 sand to predict permeability and mould hardness**

| Trial No | Sodium Silicate | Coal Dust | Mixing Time | Gassing Time | Permeability (Exp) | Permeability (ANN) | Error (%) |
|---|---|---|---|---|---|---|---|
| 1 | 4 | 2 | 5 | 30 | 550.66 | 555.86 | -0.94 |
| 2 | 6 | 2 | 5 | 30 | 610 | 600.43 | 1.56 |
| 3 | 6 | 0 | 5 | 9 | 263.5 | 269.59 | -2.31 |
| 4 | 6 | 2 | 5 | 34 | 650 | 600.43 | 7.62 |
| 5 | 6 | 3 | 8 | 30 | 226 | 212.77 | 5.85 |
| 6 | 8 | 2 | 5 | 32 | 780 | 733.38 | 5.97 |

## 4. DISCUSSION OF RESULTS

Back propagation neural network is not only capable of modeling highly non-linear relationship using dispersed data in the solution domain. No theoretical base exists for deciding the number of hidden layers, number of neurons, learning rate etc ….[1].Magnitude of most of the experimental results are very small and in majority cases the value is leaning around one and hence a stringent mean square error goal i.e. 0.0001 is fixed as terminating condition .Published literature reveals that such a fine tuning of targeting error demands considerable period of training [6] .But by adjusting the number of neurons appropriately in the successive hidden layers and also judiciously selecting the learning and momentum rate made the successful training of ANN possible in reasonably good period of time. In case of ANN model of $CO_2$

mould made of reclaimed $CO_2$ sand the different configurations of architectures tried are: 4-10-8-5, 4-20 -18 – 5 etc--- Different learning rates and momentum rates for each of the considered configurations of the ANN are tried. It is observed that the higher the learning rate lesser the number of cycles required for completion of training. This is in tune with the findings of Mohammed A .Otair et al [7] .But if the learning rate is increased beyond a certain limiting value fluctuations are observed in the mean square error versus number of learning cycles curve, which is not desirable i.e the learning rate should not be increased for lesser number of cycles of learning at the expense of prediction capability of the ANN. Ultimately the success is achieved at the configurations of 4-48-38-5 with a learning rate of 0.8 and a momentum rate of 0.8 The mean square error versus learning cycles graph for reclaimed sand is shown in figure 2. This figure indicate that the training and validation errors decays continuously from a higher value and reaches to targeted error after 1570 cycles for reclaimed sand. Similar experience i.e completion of training in 300 epochs(learning cycles) is reported by A. Mandal [1] This is possible due to judiciously selecting various parameters of ANN like number of layers, number of neurons, learning rate, momentum rate etc Otherwise in some of cases even after few lakhs of cycles also the error (may be training and validation) did not settle down into specified error band The training and validation graph shown in Figure 3 reveals that the difference between predicted value and experimental value is within the acceptable range .In few cases errors are above 20%.This can be justified as the experimental values are small and even a small deviation in predicted value can result into high percentage of error. The ANN model developed for reclaimed sand is more successful in training and validation adequately trained ANN for both fresh and reclaimed sand is tested for judging its ability to make predictions. Though testing is made for all considered characteristics, in present paper only testing of permeability is presented (Table-2) it can be observed that the developed ANN for reclaimed $CO_2$ sand has gone through the testing successfully. In majority cases the error is less than 10% and in very few cases the error leans around 20%.Literature reveals that sometimes-abnormal values may be registered during testing but in the present work no such instances are found.

## 5. CONCLUSIONS

$CO_2$ moulds made of reclaimed $CO_2$ sand has been effectively modeled using ANN. Fixing of appropriate configuration of network to a specific pattern of data is the most difficult task and this is to be obtained by trial and error method. As the learning rate of the ANN is more the training completes in lesser period of time. Configurations of the developed ANN Models for $CO_2$ mould made of Reclaimed $CO_2$ sand is 4-48-38-5 with a learning rate of 0.8 and a momentum rate of 0.8 Developed ANN model shows good match with experimental results.

## REFERENCES

1) A .Mandal and P.Roy "Modelling the Compressive Strength of Molasses- Cement Sand System using Design of Experiments and Back propagation Neural Networks", journal of Material Processing and Technology, December 2006,pp 167-173

2) A.D Sarkar "Collapsibility of Silicate bonded sands " Foundry Management & Technology ,Vol 90,Aug 1962,pp-52
3) D.S Leidel , "Reclamation of Sodium Silicate Bonded Sand " AFS Transaction, Vol 99 ,pp 429-434
4) B.Polasek. I. Garaj and L.Veley. "Dry-Reclamation of Self Setting Sodium Silicate Bonded Sands hardened with Esterol at the Foundry of MZ Hrenee " Sleverenstvi , Vol.29, Feb / Mar 1981, pp 76-79
5) P.F Bartelt,M.R Grady and D.Dibble , "Application of intelligent techniques for green sand control " ,AFS Transactions volume 104,1996,pp 1003-10
6) D.Benny Karunakar and G.L Datta "Modelling of Green Sand Mould Parameters using Artificial Neural Networks", Indian Foundry Journal Vol 49,No 12 December 2003,PP 27-36
7) Mohammed A.Otair and Walid A.Salameh "Speeding up Back Propagation of Neural Networks "Proceedings of the 2005 informing science and IT education ,June 16-19,2005,Flagstaff,Arizona .USA.
8) Carling A, "Back Propagation", Introducing Neural Networks, pp 133-154.
9) Fahlman" Faster learning variations on Back Propagation Neural Networks Algorithm applications", pp 38-51 Proceedings of connectionist model Summer school 1988.