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MODELLING OF PARAMETERS OF SILICATE BONDED CO_2 MOULD USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

CO2 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. The inherent drawback of CO2 sand moulds is poor collapsibility. A compromise is to be struck between mould hardness, permeability and collapsibility. So it is required to maintain stringent control over process parameters of CO2 moulding process, to yield the best possible quality moulds. In many instances it is difficult to perceive the trend of change of mould characteristics with respect to change in process parameter values. Hence there is a need to build up an intelligent system that can predict the characteristics of the mould with practically reasonable accuracy. Hence in the present investigation it is attempted to model process parameters of CO2 moulding process. Input parameters fed to the Artificial Neural Network model are percentage of sodium silicate, quantity of CO2 gas, mixing time, and percentage of coal dust. Output expected from Artificial Neural Network are mould hardness, permeability, compression strength, collapsibility and tensile strength .For training the Neural Network properly, adequate experimental data with the help of meticulously structured experimental design is collected using a well-calibrated, precision sand testing equipment. Required network architecture is developed. It is observed that the network is trained well enough and validated the results within 2100 cycles. Predictive capability of the developed Artificial Neural Network is demonstrated through a separate experimentally obtained testing data and the results are very much encouraging.

Keywords: Artificial Neural Networks, CO_2 moulding, Sodium Silicate

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 with in 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 (ANN).

1.1 Importance of Moulding Sand Reclamation

To meet the global standards, quality of the casting is of paramount importance. Though many casting process are developed, sand moulding has its own contribution towards total global casting production. One need not over emphasize the importance of silicate bonded CO2 moulding process. Owing to its high mould hardness [2] CO2 process is widely used for casting the various metals and alloys and especially high-density alloys like steels. The inherent drawback of CO2 process is poor collapsibility[3]. It is necessary to build moulds of good quality for obtaining sound and defect free castings.. 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. A compromise is to be struck between mould hardness, permeability and collapsibility Hence it is required to control the process parameters of the sand moulds to yield the best possible quality moulds.To control these properties a stringent control is to be exercised over the process parameters of CO2 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. 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 [1,4]. In the present work it is attempted to model the process parameters of a CO2 mould using Artificial Neural Networks. ANN are best suited when the system that needs to be controlled has some of the following characteristics i. noisy data ii. Non-linear iii. Multivariate (multiple inputs and outputs) iv. System cannot be adequately modeled with traditional methods v. effect of all inputs is not completely understood [5]. Silicate bonded CO2 moulding process meets many of the afore mentioned characteristics and hence it is attempted to model the properties of the CO2 mould made of reclaimed CO2 sand through ANN

2. OBJECTIVE

To develop an intelligent Artificial Neural network model that can predict the characteristics of CO2 gas cured silicate bonded sand moulds. Important input parameters fed to the Artificial Neural Network model are percentage of sodium silicate, quantity of CO2 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) Development of network architecture suitable for the purpose i.e. 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
iii) Testing of Neural Network

3.1 Obtaining the Experimental Data

As much experimental data as possible about the process parameters and the concerned mould characteristics is to be obtained. The utility of the neural network depends on the accuracy with which the experiments are conducted. AFS standard sand specimens of size 2”x2” are prepared using the sand rammer [6]. 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 characteristics 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 silicate 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 CO2 gas is appropriately converted in to gassing time) and mixing time is varied between 5 to 10 minutes. The input parameters for each experimental trial combination and corresponding results are given in Table1.

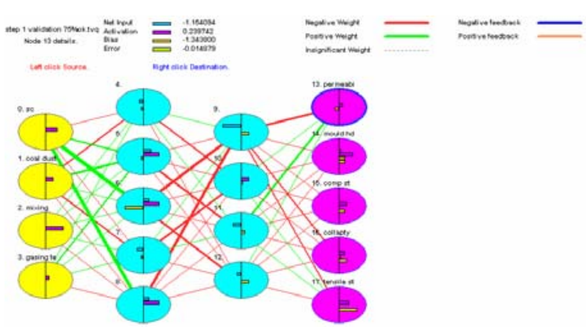

Fig 1: Network architecture (Representative figure)

Experimentally obtained data of Table-1 is normalized using the following equation

$$v' = \frac{v - \min A}{\max A - \min A}(new\_\max A - new\_\min A) + new\_\min A$$

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

3.2 Fixing the Network Architecture and Training

Out of the whole experimental data few sets of data are randomly chosen for the purpose of validation. Back propagation learning algorithm, due to its wide acceptability [7,8] ,is employed to train and validate the data set for the current problem. Back propagation neural network 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. Multi layer perceptron with two hidden layers can often yield an accurate approximation with fewer weights than that of MLP with one hidden layer. A network with one hidden layer may reach the specified error goal in a less time but may not perform well during validation and testing[4]. Initially single hidden layer is attempted but a miserable failure is experienced in validation. Similar experience is faced even with increased number of neurons in the considered single hidden layer. It is reported that ANN with three hidden layers takes considerably longer period of time and prediction is outside the acceptable range due to over fitting.[4].Hence two hidden layers are considered and the success is achieved in the present work. Learning and momentum rates are fixed by trial and error method. Training and validation process of the network terminates when mean squared error goal of 0.0001 is achieved. As the exact network model could not be accommodated in one page the representative figure of the developed ANN is given in Fig-1. Graph showing the mean squared error versus learning cycles is given in Fig-2 ad training and validation graphs are given in Fig-2

Table 1: Details of input parameters of various experimental trial combinations conducted and their results to model CO2 mould made of Reclaimed sands**.**

Trial no	***Sodium silicate***	***Coal dust***	***Mixing time***	***Gassing time***	***Mould Hardness No (Dimension less)***	***Permeability No (Dimension less)***	***Compression Strength x 10^{-3} (N/m^2)***	***Collapsibility Strength x 10^{-3} (N/m^2)***	***Tensile Strength x 10^{-3} (N/m^2)***
1	3	0	5	8	39	750	0.4	0.28	0
2	3	1	6	13	62.33	260.66	1.12	1	0
3	3	2	7	20	59.5	194.66	1.1	0.48	0
4	3	0	8	22	42	440	0.68	0.96	0.4
5	3	2	10	28	58.66	275.66	2.85	0.6	0.4
6	3	0	5	26	46.33	418.33	0.76	1	0
7	3	1	7	28	58	193.33	2.34	0.96	0
8	3	2	10	30	61.66	183.66	3.67	0.68	0.4
9	4	0	5	8	56	623.33	2.44	1.88	0.6
10	4	2	7	20	62	440	2.6	1.16	0.8
11	4	1	10	28	75	349.5	8.05	4.44	1.2
12	4	2	5	26	61.33	505.66	2.44	0.76	0.8
13	5	0	5	8	58	440	3.97	2.6	0.6
14	5	1	6	13	69	250.5	4.02	3.82	0.7
15	5	2	7	20	62	331	2.72	1.21	0.7
16	5	0	8	22	61	349.44	3.99	3.1	0.6
17	5	1	10	28	78	323	5.1	5.32	1
18	5	2	5	26	72	399.33	4.43	3.72	1.6
19	5	0	7	28	67	331	5.2	9.04	0.8
20	6	0	5	8	69.33	267.66	4.12	4.76	0.8
21	6	1	6	13	78.33	246.33	4.46	4.16	1.6
22	6	2	7	20	78	241.33	4.94	3.98	0.8
23	6	0	8	22	80.33	260.66	5.2	4.44	1.4
24	6	1	10	28	86	271.66	7.34	7.84	1.6
25	6	2	5	26	79	623.33	6.63	3.2	1.4
26	6	0	7	28	82	561.66	7.54	9.2	1
27	7	2	7	20	80	226	0.1	4.32	0
28	7	1	10	28	13.5	172.66	0.1	0	0
29	4	0	5	13	71.66	522.33	4.48	2.3	0.9
30	4	2	10	13	64.33	463.33	4.186	2.906	1.06
31	4	0	10	30	72.66	750	3.48	4.36	0.93
32	6	2	5	13	80.33	96	5.54	3.32	1.43
33	6	0	10	13	77.66	275	5.12	6.84	1.16
34	6	0	5	30	81.6	242.33	5.48	5.48	1.33
35	6	2	10	30	77.33	212.33	5.23	3.11	2
36	5	0	10	22	73.33	217.33	2.44	9.68	1.4
37	5	1	5	30	80	238.33	5.04	4.98	1
38	6	2	5	22	72	318	2.65	1.68	1
39	6	0	7	30	78	323.33	4.89	9.88	1.4

Table 2: Testing of ANN model developed for CO2 mould made of fresh silica sand to predict Permeability and Mould hardness

Trail no	***Sodium silicate(%)***	***Coal dust(%)***	***Mixing time (minutes)***	***Gassing time (secds)***	***Permeability (experimental)***	***Permeability (ANN prediction)***	***Error(%)***	***Mould hardness (experimental)***	***Mould hardness (ANN prediction)***	***Error(%)***
1	4	2	5	30	467	420.46	9.96573	65.33	66.64	-2.0052
2	6	2	5	30	525	611.71	-16.5	81	78.85	2.65432
3	6	0	5	9	270.33	279.88	-3.5327	69.84	68.57	1.81844
4	6	2	5	34	640	614.9	3.92187	77.33	78.80	-1.9125
5	6	3	8	30	525	481.39	8.30666	68	65.56	3.58823
6	8	2	5	32	650	701.53	-7.9276	78.66	76.4	2.87312

Table 3: Testing of ANN model developed for CO2 mould made of fresh silica sand to predict Compression strength and Collapsibility (retained strength)

Trial no	***Sodium silicate (%)***	***Coal dust(%)***	***Mixing time(minutes)***	***Gassing time(seconds)***	***Compression strength x 10^{-3} (N/m^2) (experimental)***	***Compression strength x 10^{-3} (N/m^2) (ANN prediction)***	***Error(%)***	***Collapsibility (experimental) x 10^{-3} (N/m^2)***	***Collapty (ANN prediction) x 10^{-3} (N/m^2)***	***Error(%)***
1	4	2	5	30	3.76	3.25	13.56383	0.61	0.99	-62.2
2	6	2	5	30	6.89	6.41	6.966618	3.98	4.41	-10.804
3	6	0	5	9	4.12	4.14	-0.48544	4.46	4.1805	6.26681
4	6	2	5	34	6.48	6.43	0.771605	4.1	4.44	-8.29
5	6	3	8	30	4.39	3.874	11.75399	0.92	0.8333	9.45
6	8	2	5	32	5.32	6.12	-15.0376	3.37	3.75	-11.276

Table 4: Testing of ANN model developed for CO2 mould made of fresh silica sand to predict Tensile strength

Trail no	***Sodium silicate (%)***	***Coal dust (%)***	***Mixing time (minutes)***	***Gassing time (seconds)***	***Tensile strength x 10^{-3} (N/m^2) (experimental)***	***Tensile strength x 10^{-3} (N/m^2) (ANN prediction)***	***Error(%)***
1	4	2	5	30	1.16	1.02	12.06897
2	6	2	5	30	1.64	1.57	4.268293
3	6	0	5	9	0.8	0.76	5
4	6	2	5	34	1.48	1.57	-6.08108
5	6	3	8	30	1.9	1.64	-17.9856
6	8	2	5	32	1.02	1.13	-10.7843

3.3 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 percentage with respect to the experimental values are shown in Table-2,3, &4.

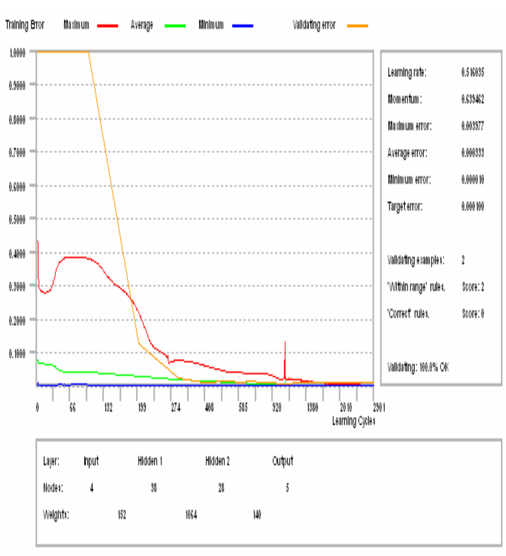

Fig 2: Graph showing the Mean squared error vs. learning cycles

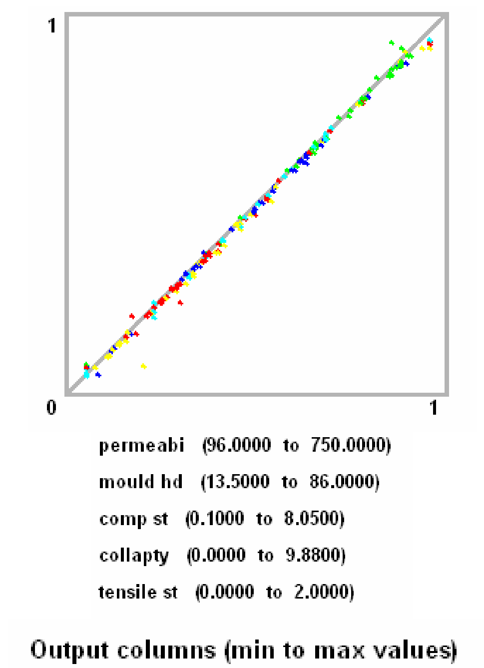

Fig 3: Training and validation graphs

4.0 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**.** [4]. 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 CO2 mould made of fresh silica sand the different configurations of architectures tried are : 4 – 10 – 8 - 5 , 4-20 – 18 – 5 .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 **[9].** 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 4-38-28-5 with a learning rate of 0.51 and a momentum rate of 0.63 . The mean square error versus learning cycles graph for is shown in figure 2. This figure indicates that the training and validation errors decays continuously from a higher value and reaches to targeted error after 2100 cycles**.** 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 or 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 with in 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.. Adequately trained ANN model is tested for judging its capability to make predictions. Error percentage between experimental values and ANN predictions for mould hardness, permeability, compression strength, collapsibility and tensile strength are given in Table-2,3 and 4. It is observed that the developed ANN has gone through the testing successfully. In majority cases the error is less than 10% and in very few cases the error leans around 15%. Literature reveals that sometimes-abnormal values **[4]** may be registered during testing but in the present only one such instances is found. Authors of paper also attempted to determine optimum condition of process parameters for each of the mould characteristics(mould hardness, permeability etc..) using the developed ANN and compared the obtained optimum condition with the optimum condition of process parameters obtained through Taguchi technique .It is observed that the optimum condition obtained through ANN is much more accurate .However the comparison of optimum condition through ANN and Taguchy are beyond the scope of this paper.

5. CONCLUSIONS

Process parameters of CO2 moulding process have been effectively modeled using Artificial Neural Network. 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 CO2 mould is 4-38-28-5 with a learning rate of 0.51 and a momentum rate of 0.63. Developed ANN model shows good match with experimental results and can be successfully used for setting the process parameter to prepare a good quality CO_2 mould and inturn good quality castings.

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7. REFERENCES

1. A.Mandal and P.Roy "Modeling 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 "Foundry core and mold making" U.K, Pergaman press 1964
3. A.M.Lyass and I.V Vallsovskil,"Improving the Knock Out Properties of Silicate Bonded Mixtures"Russian Castings Production,1960,pp410-414.
4. D.Benny Karunakar and G.L.Datta "Modeling of Green Sand Mould Parameters using Artificial Neural Networks", Indian Foundry Journal, volume 49, No 12, December 2003, pp 27-36
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.) AFS mould and core test Hand book, pp 187-318, American Foundry men's society, Inc….. Des plains , II (1989)
7. Fahlman, "Faster learning variations on back propagations: An empirical study", Proceedings of the connectionist model summer school, 1988, pp 38-51.
8. Freeman.J.A and Skapura.D.M, "Back propagation neural networks algorithm applications and programming techniques", 1992, pp89-125.
9. 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.