Modelling of Process variables for fly ash based Al-6063 composites using Artificial Neural Network

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Abstract - In this paper predictive model for Metal Matrix Composite (MMCs) has been developed with the use of Artificial Neural Network. Stir casting process has been used to fabricate the fly ash based AL-6063 particulate MMC. The hardness of fly ash based AL-6063 MMC is taken as output variable, however fly ash(FA) percentage of reinforcement in MMC, stirring speed of stirrer and pouring temperature of liquid phase of particulate reinforced MMC are considered to be input variable. This work is divided into two phases, in first phase twelve set of experiments have been performed with above mentioned input-output variables. Using these results artificial neural network has been trained with the help of feed forward back propagation technique in second phase. Maximum hardness of value 44.24 at 9 % of FA percentage at 730° C pouring temperature with 350 rpm stirring speed of stirrer was predicted through this model.

Index Terms: Artificial neural networks, feed forward back propagation technique, Hardness, particulate MMC, stir casting.

I. Introduction

METAL MATRIX COMPOSITES (MMCs) are considered as a group of newly advanced materials for their high strength and specific modulus, lightweight, low coefficient of thermal expansion, good wear resistance properties, high specific stiffness, superior elevated temperature properties. These composites containing particulate reinforcements often tend to exhibit clustering of the reinforcement particles depending upon the processing route adopted to produce the material [1]. Manufacturing of behaviour alloy based casting composite materials via stir casting is one of the prominent and economical route for development and processing of metal matrix composites materials [2].

Stir casting is one of the simplest ways of producing behaviour matrix composites. However, it suffers from poor incorporation and distribution of the reinforcement particles in the matrix. These problems become especially significant as the reinforcement size decreases due to greater agglomeration tendency and reduced wettability of the particles with the melt [3]

The most commonly used metal matrix composite consists of aluminium alloy reinforced with hard ceramic and soft particles. These hard ceramic particles are silicon carbide, alumina [4, 5], however soft particles are graphite, talc *etc* [6, 7]. These materials have different strengthening mechanisms when compared with conventional materials or continuously reinforced composites [8].

Although various authors have reported their contributions in the area of MMC, despite lack of generic predictive model has been observed for MMC. Keeping these view, attempt has been made by authors to develop a predictive model for MMC.

Artificial neural networks (ANNs) are comparatively new behaviour techniques, which can be used to solve problems that are difficult for conventional computers or human beings. ANN is a parameterize model used for empirical regression and classification and its flexibility makes it able to discover more complex behaviours than traditional statistical models [9] Unlike traditional models which a specified relationship must be chosen before analysis, ANN is a general regression method and trained on a set of examples of input and output data [10] The result of this training is a set of weights that by combining with specified functions, represents the trend between inputs and outputs. Therefore, the training is a search procedure in the weights space for the best nonlinear representation of data behaviour. Once the network trained and the relationship determined estimation of new outputs for given inputs is straightforward.

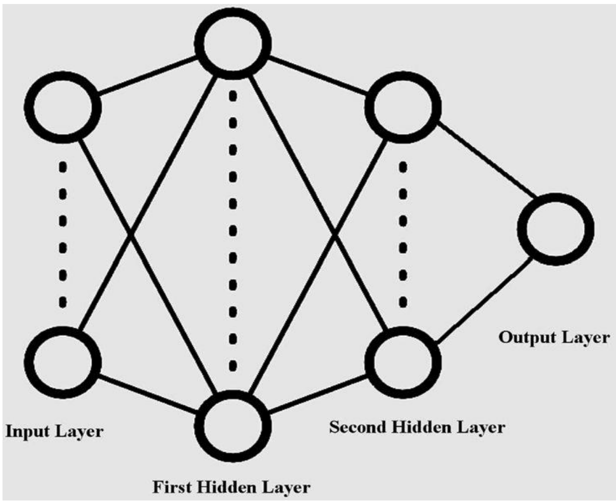

Figure1. Schematic architecture of artificial neural network [11]

A feed forward network composes of an input layer, one output layer and hidden layer(s) which the number of neurons in hidden layer(s) only, is in our control and indicates the model complexity. Arrangement of layers and units in an ANN called architecture [12]. Figure 1 sketches schematic architecture of a feed forward ANN model. In each layer, units receive their input from previous layer's units and send their output to units in the following layer. Output of each hidden unit is the transfer function response to the weighted sum of its inputs. In this work, the nonlinear hyperbolic tangent transfer function and linear transfer function was used as hidden unit and output unit respectively.

II. EXPERIMENTAL

Preparation of the composite

Table 1 Composition of Al-6063 (wt pct)

Metal	**Si**	**Fe**	**Cu**	**Mn**	**Mg**
% composition	0.2 - 0.6	0.0-0.35	0.0-0.1	0.0-0.1	0.45-0.9
Metal	**Zn**	**Ti**	**Cr**	**Al**	
% composition	0.0-0.1	0.0-0.1	0.1 max	Balance	

The particulate reinforcement aluminium metal matrix composite (PRAMMC) selected for the present investigation was based on Al-Mg matrix alloy, designated by the aluminium association as Al-6063. This matrix alloy was chosen since it provides excellent combination of strength and damage tolerance at elevated and cryogenic temperatures. The Fly Ash (FA) particles which were used to fabricate the composite have average particle size of less than 40µm and average density of 2.5 mg/m^3. The nominal chemical composition (in wt pct) of the matrix alloy is given in table 1.

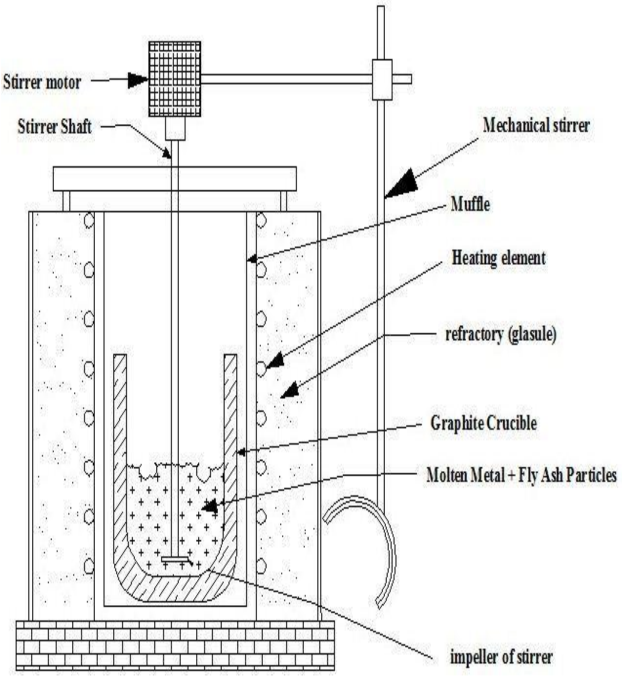

Figure2. Experimental set-up for preparation of composite

Stir casting technique is most economical to fabricate composites with particulates fibres **[**13]. For fabrication of this composite, the pouring temperature values are varied (720ºC, 740ºC, 760ºC). FA particle reinforcement varied from 0 to 9 wt pct. The other input parameter (stirrer speed) is also varied (200rpm, 300rpm, 400rpm).It is to be mentioned that the value of these above mentioned input variables have been considered after trial and error basis. Other ranges of these variables were also used in experiment but due to non-homogeneity with liquid phase and spread of reinforcement (fly ash) not considered for fabrication of composite. In this process matrix alloy (Al-6063) temperature was lowered gradually below the liquidus temperature to keep the matrix alloy in semi- solid state. At this temperature the preheated F.A particles were introduced into slurry and mixed. The composite slurry temperature was increased to fully liquid state and automatic stirring was continued for 5min. at defined stirring speeds of 200rpm, 300rpm, and 400rpm. The melt was then superheated above liquidus temperature and finally poured at defined temperature range into the mild steel permanent mould of 25mm diameter and 150mm in height. Pictorial View of experimental set up for fabrication of fly ash based Al-6063 MMC through above mentioned procedure is shown in Fig.2.

A Vickers hardness testing machine is used to measure the micro hardness of the fly ash composite samples. The specimens of 20 x 20 x 20 mm were cut from cast samples and then polished metallographic ally. During the test the diamond pyramid indenter with certain shape is penetrated into the surface of the specimens under certain test force which shall be removed after retained for certain period of time. After measuring the length of the diagonal lines of the indentation, the hardness value is gained by looking up chart as per length of the diagonal lines or by formula [14]:

$$HV = \frac{1.8544\,F}{d^2} \quad Kgf/mm^2 \qquad (1)$$

Plan of experiments

The experiments were conducted as per the standard orthogonal array. The election of the orthogonal array was based on the condition that the degrees of freedom for the orthogonal array should be greater than or equal to sum of those hardness parameters [15-16]. The hardness of fly ash based AL-6063 MMC is taken as output variable, however fly ash (FA) percentage of reinforcement in MMC, stirring speed of stirrer and pouring temperature of liquid phase of particulate reinforced MMC are considered to be input variable, which has also been mentioned in previous section. Table 2 indicates the factors (Input Variables) and their level (different set of values for these variables). The experiment consists of 9 sets (each row depicts the one experiment; however each column depicts parametric values in *L*9 orthogonal array). Pouring temperature (*T* ºC); stirring speed and reinforcement (fly ash %) are assigned to first, second and third column respectively. The last column of table shows output variables namely hardness in Vickers. The experiments were conducted as per the orthogonal array with level of parameters given in each row.

Table 2 Experimental data using L_9 Orthogonal Array

Set	**Pouring Temperature (T ºC)**	**Stirring speed rpm**	**Reinforcement (FA %)**	**Hardness in Vickers**
1	720	200	3	29.6
2	720	300	6	34.0
3	720	400	9	42.9
4	740	200	6	38.9
5	740	300	9	42.1
6	740	400	3	28.8
7	760	200	9	41.1
8	760	300	3	28.0
9	760	400	6	34.7

III. DEVELOPMENT OF PREDICTIVE MODEL USING ANN

Artificial neural network

Neuron is the main ingredient of Human Nervous System. Artificial neuron imitates the activity of neuron. It is a computational model inspired in the Artificial Neural Network. Figure3 shows natural neurons receive signals through synapses located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse, and might activate other neurons [17].

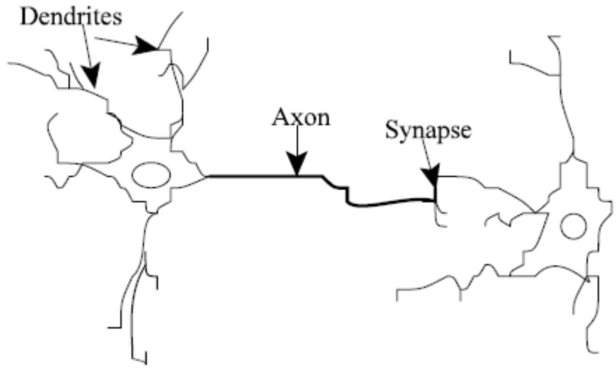

Figure 3. Natural neurons (artist's conception) [17]

Artificial Neural Network is iterative procedure to produce the result in terms of output. The iterations are high in number to readjust the weights on each neuron on the network. The weights are readjusted again and again to obtain least Mean Squared Error.Back propagation algorithm (Rumelhart and McClelland, 1986) is used for adjusting the appropriate weights on all neurons of network. [18]

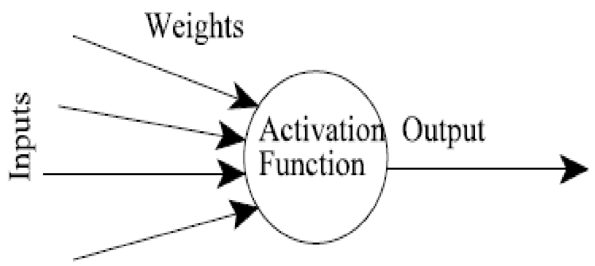

Figure4. An artificial neuron [17]

Figure4. Shows, weights are assigned with each arrow, which represent information flow. These weights are multiplied by the values which go through each arrow, to give more or less strength to the signal which they transmit. The neurons of this network just sum their inputs. Since the input neurons have only one input, their output will be the input they received multiplied by weight.

The Back propagation Algorithm

The back propagation algorithm (Rumelhart and McClelland, 1986) is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layers. The back propagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the back propagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.

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The activation function of the artificial neurons in ANNs implementing the back propagation algorithm is a weighted sum (the sum of the inputs x multiplied by their respective weights w) we can see that the activation depends only on the inputs and the weights. If the output function would be the identity (output=activation), then the neuron would be called linear.

Predictive Model using ANN

Nine sets of experiments have been performed using L-9 orthogonal array and results in terms of input-output relations have been given in Table2 in previous section. However it has been reported [19] that generally twelve (12) sets of input-output relationships are required for accuracy in training. Keeping this view three (3) more number of experiments has been performed and their results in terms of input-output relationship are given in Table3.

Table3 Input-output variables for ANN model

Test no	Pouring Temperature (T °C)	Stirring speed rpm	Reinforcement (F.A %)	Hardness in Vickers
1	720	300	9 %	40.0
2	740	400	6 %	32.0
3	760	200	3 %	29.9

All these Input-output relationships (12 numbers) obtained through experimental data have been used for training the network. Input and output variables are normalized and fitted to Neural Network for training. Training is concerned with adjustment of weights among neurons. Input data has three (3) variables pouring temperature of liquid phase, stirring speed of stirrer, percentage of fly ash reinforcement %), while the output data has one variable namely hardness of fly ash based Al-6063 composite. The various parameters (Number of Hidden Layer, Number of Neurons in each hidden layer, Learning rate, momentum, Mean Squared error, transfer function) concerned with training of ANN are adjusted through trial and error procedure. Following this two hidden layers with nine (9) neurons in each have been considered using Back propagation algorithm for training. Hyperbolic tangent sigmoid (tansig) transfer function is used for hidden layers, however linear transfer function (purelin) is used at the output layer. The momentum and learning rate are taken to be 0.7 and 0.25 respectively. The mean squared error was set as 0.00001. Initially number of iterations was taken in the range of 30000 to 42000. Finally it has been seen 40000 iterations provide required MSE value so often. Hence 40000 iterations have been considered for this model. Training ended once the Mean squared error (MSE) was reduced to 0.00001 or the number of iterations reached to 40000.

Table4 Predicted values of output through Developed ANN based Model

Sr. No.	Pouring Temperature (T°C)	Stirring Speed (rpm)	Fly Ash %	Hardness in Vickers (HVN)
1	730	250	3.5	29.88
2	730	250	4.0	30.42
3	730	250	4.5	31.61
4	730	250	5.0	32.49
5	730	250	5.5	33.68
6	730	250	6.0	35.34
7	730	250	6.5	37.23
8	730	250	7.0	39.41
9	730	250	7.5	40.87
10	730	250	8.0	41.14
11	730	250	8.5	42.68
12	730	250	9.0	43.75
13	730	350	3.5	30.11
14	730	350	4.0	31.68
15	730	350	4.5	32.43
16	730	350	5.0	33.67
17	730	350	5.5	34.73
18	730	350	6.0	36.12
19	730	350	6.5	38.33
20	730	350	7.0	40.21
21	730	350	7.5	41.10
22	730	350	8.0	42.63
23	730	350	8.5	43.13
24	730	350	9.0	44.24
25	750	250	3.5	27.43
26	750	250	4.0	29.23
27	750	250	4.5	31.26
28	750	250	5.0	32.89
29	750	250	5.5	33.12
30	750	250	6.0	34.24
31	750	250	6.5	35.45
32	750	250	7.0	36.91
33	750	250	7.5	38.12
34	750	250	8.0	39.45
35	750	250	8.5	41.33
36	750	250	9.0	42.61
37	750	350	3.5	29.91
38	750	350	4.0	31.11
39	750	350	4.5	32.23
40	750	350	5.0	33.03
41	750	350	5.5	34.12
42	750	350	6.0	35.43
43	750	350	6.5	36.63
44	750	350	7.0	37.72
45	750	350	7.5	38.67
46	750	350	8.0	39.91
47	750	350	8.5	41.20
48	750	350	9.0	42.78

The output values may be predicted using this model, for different values of input variables. Some of the results in terms of input-output relationship for this predictive model are shown in Table4 It can clearly be seen that maximum value of hardness 44.24. Many other combinations of input variables were also tried, but not being reported due to non-improvements in results (Maximizing the Hardness).

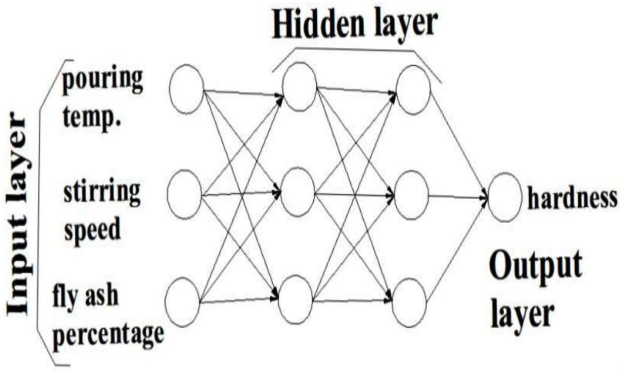

Figure5 ANN Architecture

The architecture of neural network used in this investigation shown in Figure5. Performance of the ANN model is illustrated when experimental data were given as input to network of the model. These data were further divided into three parts training, testing and validation by Network itself. It can be seen through Fig.6 to Fig. 8 c that developed ANN model performs reasonably good for prediction of hardness of fly ash based Al-6063 based MMC.

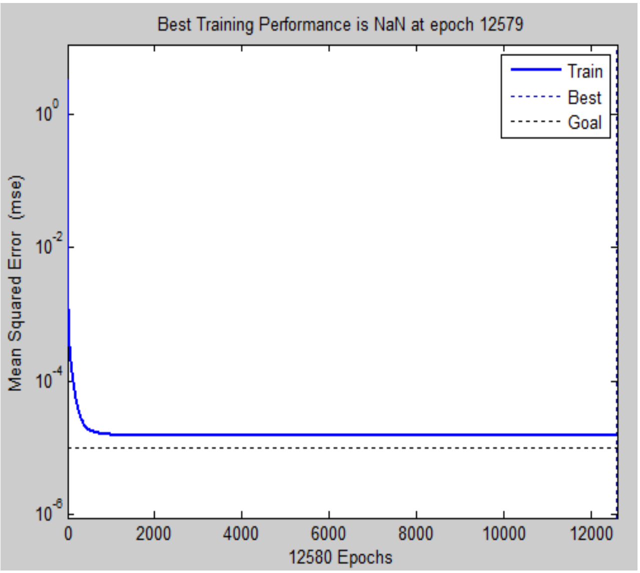

Figure6 Mean Squared Error for the network

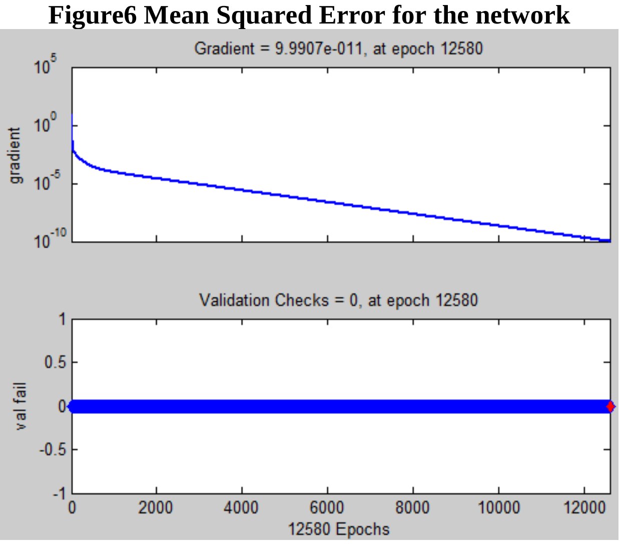

Figure7 Gradient during ANN training

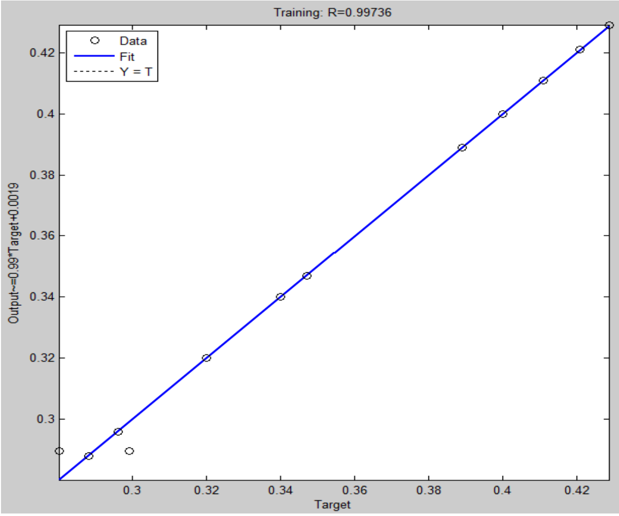

Figure8 Regression analyses of data used for training

Figure6 shows the error is minimized by increasing the epochs. Figure7 shows the gradient during training fall continuously due to readjusting of weights of neuron in 12580 epochs. Figure8 shows the regression line of data used for training. The highly trained data is closer to regression line. This indicates reasonably good performance of the network.

IV. CONCLUSION

Experiments were performed for fabrication of fly ash based Al-6063 composite. Three process variables stirrer speed of stirrer, pouring temperature of liquid phase and percentage of reinforcement (fly ash) have been considered as input, however hardness in Vickers was taken to be output variable.
It has been observed through experimental data that the hardness has non linear relation with variables (Fly ash composition, Pouring temperature, Stirring speed). Hence attempt has been made to develop more accurate and computationally efficient non-parametric approaches for the prediction of Hardness in Vickers. Using these experimental input-output data ANN based model is developed. The various parameters of ANN for experimental data are adjusted on trial and error basis to minimize MSE (Mean Squared error). The ANN based modeling approach is used for accurately predicting the hardness for all possible combinations of fly ash percentage, pouring temperature, stirring speed of stirrer, so that a suitable combination of these variables may be recommended to increase the hardness.

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