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Modeling volume loss of heat treated Al 6061 composites using an artificial neural network

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Abstract

In the present study, artificial neural network (ANN) approach was used to predict the volume loss of heat treated Al 6061 metal matrix composites reinforced with 10% SiC particles and 2% graphite particles. Composite was produced using stir casting process. Volume loss of composite was measured during wear testing in a pin on disc apparatus. Microstructure examination at wear surface was investigated by Scanning Electron Microscope (SEM). In Artificial Neural Network (ANN), Multi Layer Perceptron (MLP) architecture with back-propagation neural network that uses gradient descent learning algorithm is utilized. The results clearly revealed that the developed ANN model is reliable and accurate.
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Keywords: Aluminium hybrid composites, Wear testing, Volume loss, Artificial Neural Network, Multi Layer Perceptron;

1. Introduction

Sharma S C,(2001), Rosso M. (2003), Lin C. B, Chang R. J (1998), Mustafa Taskin, (2007), In those papers it is observed that Metal Matrix Composites (MMC's) have attracted considerable attention as a result of their ability to provide a wide range of microstructures and properties. Heat treatment of aluminium composites can increase the

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abrasive wear resistance. Large hard particles increase more intensively the wear resistance than the smaller particles. Aluminium matrix composites containing solid lubricants such as graphite and MOS_2 showed better friction and wear performance.

Abdullah Kurt, (2009), XuLiujie (2007) Necat Altinkok (2005), Mehmet Sirace Ozerdem (2009), Paulo Davim J (2008), Mohammed Hayajneh(2009), Rapetto M. P(2009), Raghu Prasad B. K(2009), . Mandal D, (2004), In those papers it is understood that, In recent years, ANN has become a very powerful tool in modeling inter-relationships between input and output parameters of many complicated systems . It is a promising field of research in predicting experimental trends and has become increasingly popular in the last few years because of solving problems much faster compared to other approaches . Various studies on the prediction of mechanical, triboligical and physical properties of composites using ANN have been carried out. In the work carried out by XuLiujie et al. they predicted the value of hardness and abrasive wear resistance using neural network. They reported that a well trained two hidden layer network had smaller training errors and much better generalization performance in comparison to one hidden layer network. Altinkok and Rasit Koker predicted tensile strength, density and porosity of particle reinforced aluminium composites using neural network. They reported that the training process was completed with 520 iterations. The neural network prediction was in good agreement with experimental results. . Mehmet Sirac Ozerdem and Sedat Kolukisa. applied neural network to predict elongation of composites. They used MLP architecture with back propagation algorithm. They found that, the neural network successfully predicted the elongation of composite specimens . Paulo Davim et al. predicted the surface roughness of Al composite using Artificial Neural Network. They reported that, the performance of ANN prediction model was though adequate can be improved by defining more number of levels for input process parameters. Mohammed Hayajneh et al. predicted the wear loss of aluminium composites using Artificial Neural Network. A satisfactory agreement between the experimental and ANN values was obtained when the model was tested. Rapetto et al. developed neural network model to determine the relationship between the roughness parameter. They found that, the neural network was able to prove the correlation between the roughness parameters . Raghuprased et al. predicted compressive strength using neural network. They found that the proposed neural network model gave good prediction of the values. Rashed and Mahmoud predicted the wear behavior of aluminium composites using neural network. They used multilayer perceptron (MLP) network. They found that considerable savings in terms of cost and time could be obtained from using ANN models. In this research paper an attempt has been made to develop a model for the prediction of volume loss of heat treated aluminium hybrid composites. In the present work 31 experimental patterns were carried out. Out of this 24 patterns were considered to train the network and 7 patterns were used to validate the model. After attaining convergence, the trained weights are fed into the testing network model to determine the outputs for the corresponding input variables. Finally the neural network outputs are compared with the desired output values and the testing error is calculated.

Nomenclature

h	Duration in hours
°C	Temperature in degree centigrade
K	Temperature in Kelvin
A	Solutionzing time
B	Solutionzing temperature
C	Aging time
D	Aging temperature
θ	Experimental value of volume loss
θ_0	Predicted value for volume loss of heat treated composite
wt%	Weight in Percentage
y	Output function
f(x)	Output function

2. Experimental Procedures

2.1 Materials

The matrix material selected in this experimental work was Al 6061 alloy while SiC and graphite particles were used as reinforcement materials. The nominal chemical compositions of the Al 6061 alloy obtained using spectrometer is (wt.%): 0.003 Cr; 0.24 Cu; 0.16 Fe; 0.89 Mg; 0.48 Mn; 0.63 Si; 0.014 Ti; 0.007 Zn; and 97.57 Al. The average size of reinforcement particles are 75 microns.

2.2 Fabrication of composites

The aluminium hybrid composite was fabricated by liquid metallurgy route [15]. Al 6061 alloy was melted in an electric furnace at 1073 K. When it reached the molten state a stirrer driven by a motor is introduced into the molten metal and a vortex was created on the top surface. A preheated silicon carbide and graphite particle was introduced into the vortex of the molten alloy after effective degassing. Mechanical stirring of the molten alloy for duration of 10 min was achieved by using graphite impeller. A stirring speed of 400 rpm was maintained. The composite slurry was then poured into a preheated cast iron mould. Then the solidified casting was removed from the mould. The cast composites were machined and subjected to heat treatment.

2.3 Heat treatment

Heat treatment of the composite was carried out using a muffle furnace as shown in Fig. 1. The sequences of operations involved during the heat treatment process of the developed composite are solutionizing, quenching, artificial aging and air-cooling [16]. The independently controllable predominant heat treatment parameters considered for the present investigation are solutionizing time, solutionizing temperature, aging time and aging temperature. The range of values for the selected heat treatment parameters are shown in Table 1.

Fig. 1 Muffle furnace

Table 1 Factors and its levels used in the experimental work

Factor	Unit	Notation	Factor level				
			-2	-1	0	+1	+2
Solutionzing time	h	A	1	2	3	4	5
Solutionzing temperature	°C	B	200	250	300	350	400
Aging time	h	C	5	6	7	8	9
Aging temperature	°C	D	120	155	190	225	260

The working ranges of all selected factors were fixed by conducting trial runs, wherein one of the factors was varied while keep the rest at constant. For the four variables chosen the design required 31 experiments with 16 factorial points, eight axial points to form central composite design and seven center points for replication to estimate the experimental error [17, 18]. The experiment has been carried out according to the run order in the design matrix shown in Table 2.

Table 2 Design Matrix for conducting wear tests

Run order	Solutionzing time (A)	Solutionzing temperature (B)	Aging time (C)	Aging temperature (D)	Experimental volume loss of heat treated composite ($\times 10^{-10} m^3$)	Predicted volume loss of heat treated composite using ANN ($\times 10^{-10} m^3$)	% Error (Experimental Value-Predicted value)/Predicted value ×100
1	-1	-1	+1	+1	39.13	38.12	2.650
2	+1	+1	+1	+1	33.42	33.66	-0.713
3	0	0	0	+2	32.45	32.70	-0.765
4	0	0	0	-2	36.20	37.30	-2.949
5	0	-2	0	0	43.14	43.99	-1.932
6	+1	+1	-1	-1	35.87	35.05	2.340
7	0	0	0	0	27.90	27.33	2.086
8	0	0	0	0	28.61	28.77	-0.556
9	0	0	0	0	27.91	28.12	-0.747
10	+1	+1	-1	+1	33.27	33.34	-0.210
11	0	0	+2	0	38.61	37.63	2.604
12	-1	-1	+1	-1	42.25	43.74	-3.406
13	+2	0	0	0	35.19	34.73	1.325
14	0	0	0	0	28.23	28.43	-0.703
15	-1	-1	-1	-1	40.49	40.16	0.822
16	0	0	-2	0	37.01	38.83	-4.687
17	0	0	0	0	29.21	29.33	-0.409
18	+1	-1	+1	-1	40.43	40.83	-0.980
19	+1	-1	-1	-1	39.70	38.09	4.227
20	0	0	0	0	28.93	28.63	1.048
21	0	+2	0	0	41.23	40.91	0.782
22	-1	+1	+1	-1	41.73	41.94	-0.501
23	-1	+1	+1	+1	38.65	39.12	-1.201
24	-2	0	0	0	40.56	41.76	-2.874
25	-1	+1	-1	-1	40.10	40.25	-0.373
26	+1	+1	+1	-1	36.21	36.80	-1.603
27	-1	-1	-1	+1	38.12	38.50	-0.987
28	+1	-1	-1	+1	34.92	36.83	-5.186
29	0	0	0	0	27.51	28.35	-2.963
30	-1	+1	-1	+1	37.76	38.46	-1.820
31	+1	-1	+1	+1	37.21	36.98	0.622

2.4 Wear tests

Wear tests were conducted using a pin-on-disc apparatus as shown in Fig. 2. The specimens were in the form of pins of diameter 10 mm and length 25 mm. Before starting of each experiment the surface of the specimen and disc is cleaned. Tests were conducted at room temperature, relative humidity of 30%, applied load of 10 N, sliding distance of 1250 m and a disc velocity of 1 m/s. Measurement of weight loss of the pin was used to evaluate the volume loss Table. 2 during the wear test. Microstructural studies were performed on the wear surface of heat treated composite samples, using a JEOL 6400 model Scanning Electron Microscope. Based on the experimental values of volume loss a mathematical model in coded form was developed using response surface methodology and is given by

$$\text{Volume loss } (Y) = 28.3286-(1.5808\times A) - (0.7942\times B)+ (0.5000\times C)- (1.3250\times D) + (2.3916\times A^2) + (3.4691\times B^2) +(2.3754\times C^2) + (1.5041\times D^2)- (0.7338\times A\times B) - (0.1112\times A\times C)- (0.1550\times A\times D)-(0.1738\times B\times C) + (0.1675\times B\times D) - (0.0075\times C\times D) \quad (1)$$

Fig. 2 Pin-on-disc apparatus

2.5 Artificial Neural Networks (ANN) modelling methodology

Artificial Neural Networks are computing systems that simulate the biological neural systems of human brain. They are based on a simplified modeling of the brain's biological functions exhibiting the ability to learn, think, remember, reason, and solve problems [19].

In the present investigation, the ANN model was developed using MATLAB R2009a software. The input parameters are solutionising time (A), solutionising temperature (B), aging time (C) and aging temperature (D). The output parameter is the volume loss of heat treated composite. The ANNs model is developed, trained and tested by using a total of 31 data sets. To test the accuracy of the models 8 of the 31 data sets were randomly selected as test sets, while the remaining 23 samples were used to train the network. The architecture of a neural network consists of a description of the number of layers, the number of neurons in each layer and how the layers connect to each other. The neuron architecture was determined in this work using a trial and error approach. After a number of trials the best network architecture and parameters that minimize the normalized root mean-squared-error (NSE) of training data were obtained as follows:

Number of neurons in the input layer = 4
Number of neurons in the hidden layer = 10
Number of hidden layers = 1
Minimum number of learning cycles = 5,000

The input and output of a neural network is in the range of zero to one to normalize their values to suit the network's functioning [20]. The normalization technique used in the proposed ANN is given in the following formula (Eq.2).

$$Normalized\ value = \frac{Inputvalue - Minimumvalue}{Maximumvalue - Minimumvalue} \quad (2)$$

The learning algorithm used in the study was gradient descent with adaptive learning rate back-propagation. Sigmoid function is the most common activation function in ANN because it combines nearly linear behaviour, curvilinear behaviour, and nearly constant behaviour, depending on the value of the input. The sigmoid function (Eq. 3) is sometimes called a squashing function, since it takes any real-valued input and returns an output bounded between [0, 1]

$$y = f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

The back propagation learning is an iterated search process which adjusts the weights from output layer back to input layer in each run until no further improvement in normalized root mean-squared-error (NSE) value is found. The error incurred during the learning process was expressed in terms of NSE (Eq. 4) used to evaluate the training performance of ANN [21].

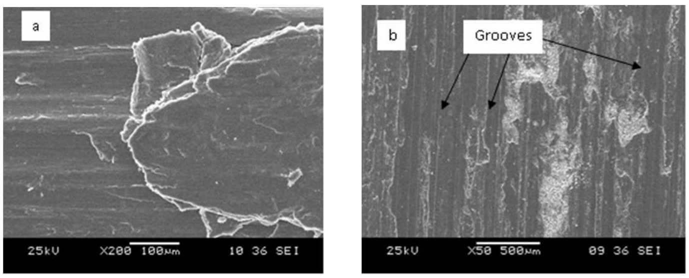
$$NSE = \sqrt{\frac{\sum(\theta-\theta_0)^2}{\sum(\theta)^2}} \tag{4}$$

When reaching the error goal, the learning process is stopped and the network is evaluated with the testing data.

3. Results and discussion

3.1 Microstructure Analysis

The microstructure of the wear surfaces of heat treated composite specimens is observed by JEOL 6400 Scanning Electron Microscope (SEM). The SEM image of the contact surfaces after sliding over a distance of 1250 m at an applied load of 10 N and a sliding velocity of 1m/s for different values of heat treatment parameters is shown in Fig. 3 (a-d). The SEM examination of the wear surfaces shows areas from where material has been removed. The microstructure showed in Fig. 3 (a&b) reveals that grooves were formed on the wear surface of the pin in the direction of sliding indicating abrasion wear. This can be due to the hard particles between the pin and the counter face act as an abrasive medium and plough the surface of the pin, causing wear by the removal of small fragments of pin material [22]. The similar observation was noticed by many researchers during the investigation of dry sliding wear of heat treated composites [23, 24]. Fig. 3 (c & d) shows delamination in the wear surfaces of pin. It involves subsurface deformation, crack nucleation and crack propagation. The large plastic strain in the deformed layers gives rise to void nucleation and subsurface crack initiation and propagation. The subsurface cracks may initiate and propagate along matrix- reinforcement interface and cause decohesion of matrix- reinforcement interface. With removal of surface material, the crack becomes nearer to the surface and the shear strain is increased, this causes the removal of the surface layers by delamination. Delamination is observed to be more severe under lower aging duration Fig. 3 (d).



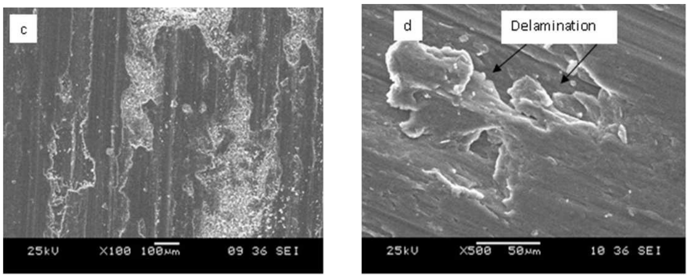


Fig. 3 (a-d) SEM examination of the wear surfaces of heat treated composites

3.2 Wear results

The volume losses calculated from the mathematical model given in Eq.1 for each set of coded factors are represented in graphical form in Fig. 5-8.
Fig. 4(a) shows the effect of solutionizing time (A) and solutionizing temperature (B) on volume loss. It is observed that the volume loss of composite decreases with increase in the value of solutionizing time upto 3h when the solutionizing temperature was from 200 to 400 °C. When the solutionizing time increases from 4h to 5h the volume loss increases. This has confirmed with the earlier findings [25, 26]. They reported that, the wear rate of composites decreases with increasing the solutionizing temperature for lower value of solutionizing time.

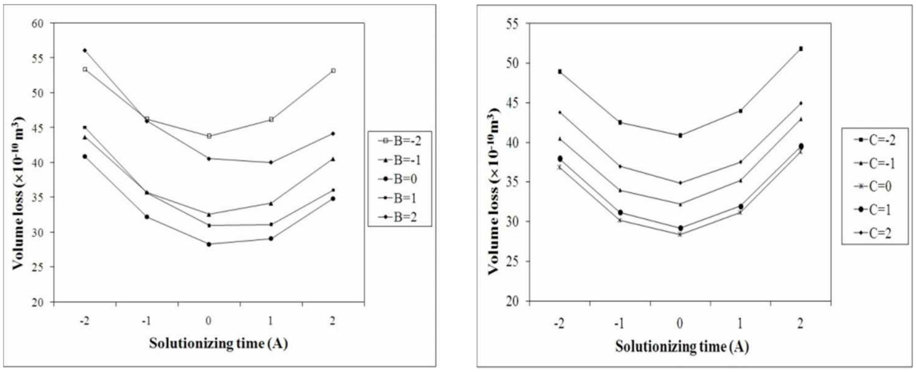


Fig. 4 (a) Effect of solutionizing time (A) and solutionizing temperature (B) on volume loss; (b). Effect of solutionizing time (A) and aging time (C) on volume loss

The influence of solutionizing time (A) and aging time (C) on volume loss is shown in Fig. 4 (b) It is clear that the volume loss decreases with increase in the value of solutionizing time up to 3h when the aging time was varied from 5 to 9h. A similar observation was observed by the researcher [27] who has stated that the wear rate of aluminium composite decreases with increasing the value of aging time up to 6h.

Fig. 5 (a) highlights the effect of solutionizing time (A) and aging temperature (D) on volume loss of composite. It is clear that the volume loss decreases with increasing aging temperature when the solutionizing time is from 1 to 3h. It can be noted that the volume loss increases with increase in the value of solutionizing time from 4 to 5h

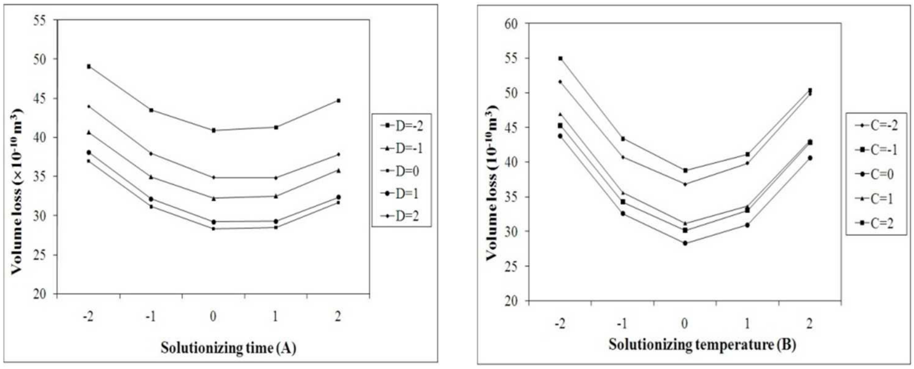


Fig. 5(a) Effect of solutionizing time (A) and aging temperature (D) on volume loss; (b) Effect of solutionizing temperature (B) and aging time (C) on volume loss

Fig. 5 (b) depicts the effect of solutionizing temperature (B) and aging time (C) on volume loss of heat treated composites. It can be observed that, when the solutionizing temperature was varied from 200 to 300 °C and the aging time varied from 5 to 9h the volume loss decreases in the range between 56 and 32×10^{-10} m^3. This observation was in agreement with the previous researcher. They reported that wear loss of the composite decreases with increasing the aging duration beyond 7h [28].

The interaction effect of solutionizing temperature (B) and aging temperature (D) on volume loss is shown in Fig. 6. It can be noted that the volume loss decreases the value between 55 and 30×10^{-10} m^3 when the solutionizing temperature was varied from 200 to 300 °C and aging temperature from 120 to 190 °C

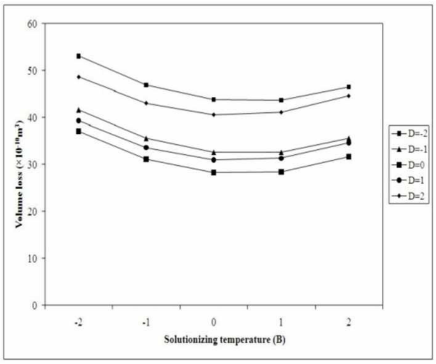


Fig. 6 Effect of solutionizing temperature (B) and aging temperature (D) on volume loss

3.3 ANN results to predict volume loss

The performance of the ANN model for predicting the volume loss of training and testing sets is illustrated in Fig. 10 and 11 respectively. It is clearly seen from Fig. 7 (a) & (b) that the experimental and predicted values developed from ANN networks for the wear rate are very close to each other. Fig. 8 (a) & (b) illustrates that the ANNs model is capable of generalizing between inputs and the output variable with high accuracy predictions. Percentage absolute errors were used to evaluate the performance of the proposed ANN in prediction technique. The prediction can be seen as fairly close to the corresponding actual values of volume loss. For trained data, it can be observed that a maximum absolute error of 5.8% and a minimum absolute error of -5.6% were obtained for volume loss prediction. Also for tested data, it can be observed that a maximum absolute error of 2.1% and a minimum absolute error of -

5.0% were obtained for volume loss prediction. However, these levels of error are satisfactory and smaller than errors that normally arise due to experimental variation and instrumentation accuracy. The results also indicated that the proposed ANNs model is successful in learning the relationship between the different inputs and the output parameter. The ANN model developed in the present work can be very useful to predict the volume loss of heat treated composites in wear testing.

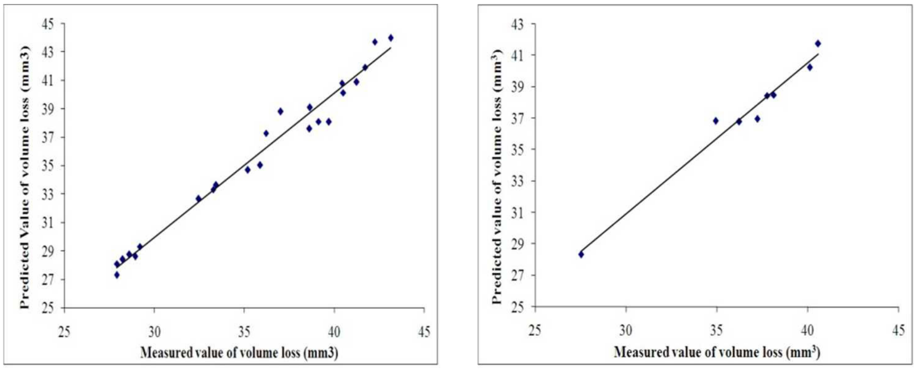


Fig. 7 (a) & (b) Performance of training set of volume loss prediction with ANN's model

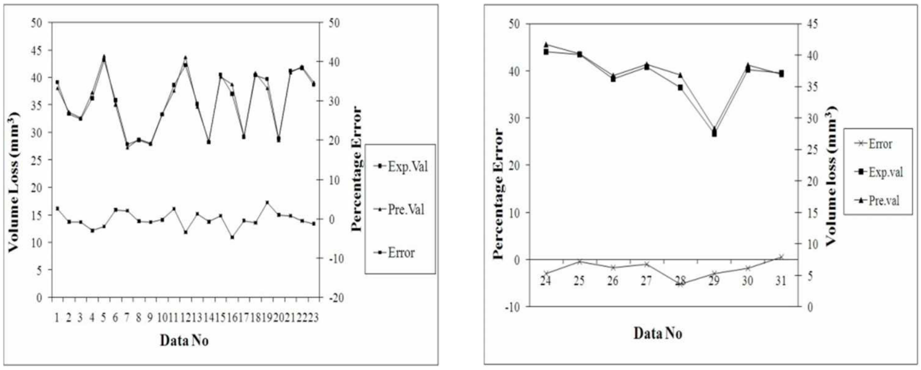


Fig. 8 (a) & (b) Comparison of predicted and actual values of volume loss of training data

4. Conclusions

The following conclusions were obtained from this experimental investigation:

- Al 6061 metal matrix composites reinforced with 10% SiC particles and 2% graphite particle is fabricated by stir casting process and the effect of heat treatment parameters on the volume loss has been investigated.
- Microstructure studies of the wear surfaces of heat treated composites clearly showed that the predominant wear mechanisms are abrasion and delimitation.
- Artificial Neural Network model to predict the volume loss was developed. The ANN gives satisfactory results when compared to the experimental readings. It also indicated that the models are reliable, accurate, and illustrate how ANNs can be used to efficiently predict the volume loss across a wide range of heat treatment parameters.
- Considerable savings in terms of cost and time could be obtained from using ANN models. ANN approach is a successful analytical tool that can be used to predict the volume loss of new materials and composites.
- Hence, it can be said that ANN can be used efficiently as prediction technique in the area of composite material characterization and tribology.

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