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ARTIFICIAL NEURAL NETWORK (ANN) APPROACH TO PREDICTION OF DIFFUSION BONDING BEHAVIOR (SHEAR STRENGTH) OF SiC_P REINFORCED ALUMINUM METAL MATRIX COMPOSITES

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ABSTRACT

In this study, Artificial Neural Network approach to prediction of diffusion bonding behavior of SiC_P reinforced aluminum alloy metal matrix composites, manufactured by powder metallurgy process, were obtained using a back-propagation neural network that uses gradient descent learning algorithm. A powder Al-Mg-Si matrix was employed with particulate SiC at 5-10-20 (wt) % fractions. MMC's were fabricated by powder mixing and hot pressing at 600ºC below liquation temperature. Diffusion bonding was carried out under protective atmosphere (argon) at 550, 575, 600 and 625ºC process temperatures for 20, 40 and 60 minutes with a load of 0.25 MPa, below those which would cause macrodeformation. Microstructure examination at bond interface were investigated by optical microscopy, SEM. Specimens were tested for shear strength and metallographic evaluations. After the completion of experimental process and relevant test, to prepare the training and test (checking) set of the network, results were recorded in a file on a computer. In neural networks training module, different SiC reinforcement fractions (wt), different temperatures and welding periods were used as input, shear strength of bonded specimens at interface were used as outputs. Then, the neural network was trained using the prepared training set (also known as learning set). At the end of the training process, the test data were used to check the system accuracy. As a result the neural network was found successful in the prediction of diffusion bonding shear strength and behavior.

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1. INTRODUCTION

Recently, with the developments in artificial intelligence; researchers have a great deal of attention to the solution of non-linear problems in physical and mechanical properties of metal alloys [Agrawal et al, 1994]. Researchers are putting much emphasis on the manufacturing, shaping, bonding problems to widespread the use of composites in common industry markets [Koker and Altinkok, 2005].

Joining of the powder metallurgy products (P/M) by diffusion bonding process is important both to protect the microstructural properties of parent materials and bonding behavior of joining materials. Aluminum-based, particulate-reinforced metal matrix composites (MMCs) are of concerns for structural carrying outs where weight saving is of primary concern. Diffusion bonding is a solid state coalescence of contacting surfaces occurs at a temperature below the melting point (0.5-0.7 T_m) of the materials to be joined with the loads and the period, below those that would cause macro deformation and a significant properties change at the parent materials. The process is depended on a number of parameters in particular, bonding temperature, atmosphere, time, pressure and surface roughness. Process pressure is selected high enough to dislocate the surface oxides. Bonding period should be selected long enough for the completion of the diffusion mechanism at the interface. Diffusion bonding is an advanced bonding process in which two materials, similar or dissimilar, can be bonded in solid state [Caligulu, 2005; Taskin, 2000].

Artificial neural networks (ANNs) have emerged as a new branch of computing, suitable for applications in a wide range of fields. Artificial neural networks have been recently introduced into tribology [Jones et al, 1997]. In this study, experimental and ANNs results have been compared. Many studies have been published in which the prediction of various parameters on aluminium alloys. Taskin et al. investigated modeling adhesive wear resistance of Al-Si-Mg-SiCp PM compacts fabricated by hot pressing process, by means of ANN [Taskin et al, 2008]. Taskin et al. investigated modelling of microhardness values by means of artificial neural networks of Al/SiCp metal matrix composite material couples processed with diffusion method [Taskin and Caligulu, 2006]. Durmus et al. investigated the use of neural networks for the prediction of wear loss and surface roughness of AA6351 aluminium alloy [Durmus et al, 2006]. Altinkok et al. investigated neural network approach to prediction of bending strength and hardening behaviour of particulate reinforced (Al-Si-

Mg)-aluminium matrix composites [Altinkok and Koker, 2005]. Chun et al. investigated using neural networks to predict parameters in the hot working of aluminum alloys [Chun et al, 1999]. Ganesan et al. investigated development of processing map for 6061 Al/15% SiCp through neural Networks [Ganesan et al, 2005].

In this study, features of multi layer perceptron architecture with back-propagation learning algorithm were employed to predict the shear strength of diffusion bonding behavior of alumininum alloys manufactured by P/M process.

2. ARTIFICIAL NEURAL NETWORK

An artificial neural network is a parallel-dispensed information proceduring system. It stores the specimens with dispensed coding, thus forming a trainable nonlinear system. Neural networks closely resemble the way human brain functions. Given the inputs and longing outputs, it is also self-adaptive to the habitat so as to respond different inputs rationally. The neural network theory deals with learning from the preceding obtained data, which is named as training or learning set, and then to check the system accomplishment using test data. Computers are an integral part of day to day activities in engineering design and engineers have utilized various applications to assist them improve their design [Perzyk et al, 2001; Rafiq et al, 2001 and Kenig et al, 2001]. ANN mimic some basic aspects of the brain functions. ANNs are based on the neural structure of the human brain, which processes information by means of interaction between many neurons and in the past few years there has been a constant increase in interest of neural network modeling in different fields of materials science. The basic unit in the ANNs is the neuron. The neurons are connected to each other with a weight factor [Limpon, 1987; Nielsen, 1998]. Artificial neural networks (ANNs) are networks of highly interconnected neural computing elements that have the ability to respond to input stimuli and to learn to adapt to the environment. ANN includes two working phases, the phase of learning and that of recall. During the learning phase, known data sets are commonly used as a training signal in input and output layers. The recall phase is performed by one pass using the weight obtained in the learning phase. ANN is now a well established tool and details about it can be found elsewhere. Various nomenclatures are used to describe neural network paradigms [Fausett , 1994 and Haykin, 1994].

Whereas, a single-layer network has single input/output units, a multi-layer network has one or more hidden units between input and output layers (Figure 1).

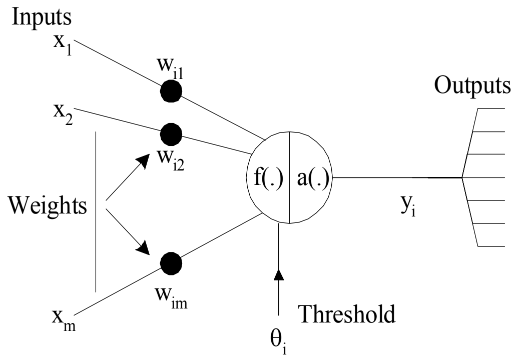


Figure 1. The mathematical model of neuron [Avci et al, 2005].

A Back Propagation (BP) Neural Network is a multi-layer neural network which uses gradient-descent technique analogous to error minimization. A neural network is characterized by the pattern of connections between the neurons; this is called the network architecture. Various network architectures are available. The information included in the illustration data was acquired via the improved back propagation (BP) learning algorithm. The parameters of the BP network were defined as follows:

The input vectors $X = [x_0, x_1, \ldots, x_n]^T$

The output vectors $[Y = y_0, y_1, \ldots, ym_l]^T$

where the symbols n, h and m represented the number of neurons in the input layer, the hidden layer and the output layer, sequentially [Avci et al, 2005].

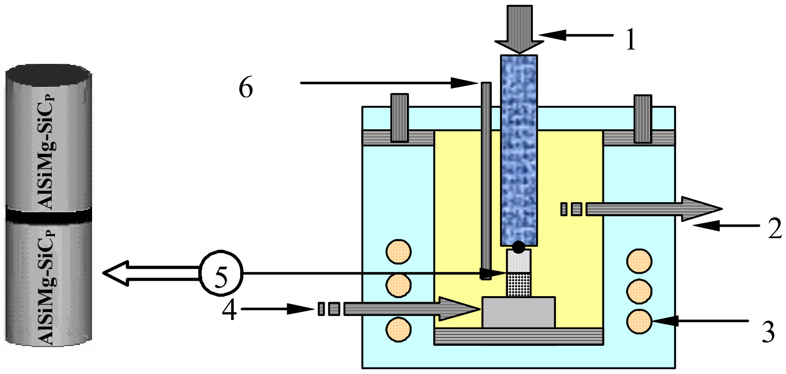
3. MATERIALS AND EXPERIMENTAL PROCEDURES

3.1. Fabrication of Al-SiC$_p$ MMCs

SiC particulate Al alloy MMCs specimens to be joined by diffusion bonding were fabricated by powder metallurgy process. 1 % Mg, 3 % Si powders were mixed with 99 % Al. SiC particles with a 42 µm mean diameter were added to the matrix at 5, 10, 20 (wt) % fractions. Powders were properly mixed with mechanic mixers for homogeneity of the formation. The mixture was cold compacted at 377 MPa in the ϕ12x60 mm steel dies. This is followed by sintering at 600ºC in argon atmosphere for 30 minutes. Finally the specimens were hot compacted and extruded at 377 MPa pressure [Caligulu, 2005].

3.2. Diffusion bonding of Al-SiC_p MMC couples

Work pieces were prepared for diffusion bonding and surfaces to be joined were protected against corrosion and oxidation. Al alloy MMC specimens with 5-5, 5-10, 5-20, 10-10, 10-20 and 20-20 % SiC (wt) fractions were coupled and bonded at diffusion bonding apparatus. Schematic illustration of diffusion bonding apparatus is given in Fig.2. Diffusion bondings were performed at 550, 575, 600 and 625 ºC process temperatures and for 20, 40 and 60 min periods under 0.25 MPa constant pressure [Caligulu, 2005].



1-Load 2-Argon Outlet 3-Heat Coil 4-Argon Inlet 5-Specimens 6-Thermocouple
Figure 2. Schematic illustration of diffusion bonding apparatus.

3.3. Microstructure examinations and shear strength tests

After the bonding process, specimens were tested for shear strength. The schematic illustration of shear strength test apparatus is given in Fig.3. Specimens were cut perpendicular to the bonding interface to facilitate longitudinal microstructure cross section examinations. Grinding of the surface was followed by etching with Keller etchant. Metallographic evaluations and investigations were made by the aid of optical microscopy and SEM.

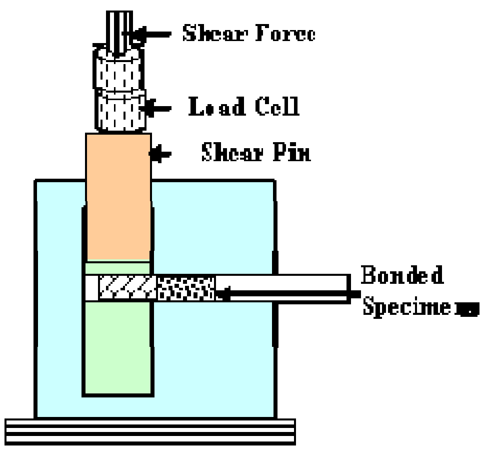


Figure 3. Schematic illustration of shear strength testing apparatus.

3.4. Modelling with neural networks

Shear strength of diffusion bonding behavior was modeled using MATLAB program. Diffusion bonding period, process temperature and SiC_p reinforcement (weight) fractions were employed as input and shear strength of the bonded interfaces were recorded as output parameters. Back propagation Multilayer Perceptron (MLP) ANN were used for training of experimental results. ANN modeling the shear strength of the interface of diffusion bonded composites were carried out with the aid of ANN block diagram given at Fig.4. MLP architecture and training parameters were presented in Table 1.

Table 1. MLP architecture and training parameters

The number of layers	3
The number of neurons on the layers	Input: 2, Hidden: 10, Output: 1
The initial weights and biases	Randomly between -1 and +1
Activation functions for hidden and output layers	Log-sigmoid
Training parameters Learning rule	Back-propagation
Adaptive learning rate for hidden layer	0.9
Adaptive learning rate for output layer	0.7
Number of iteration	5320
Momentum constant	0.95
Duration of learning time	2 minutes 8 seconds
Acceptable mean-squared error	0.001

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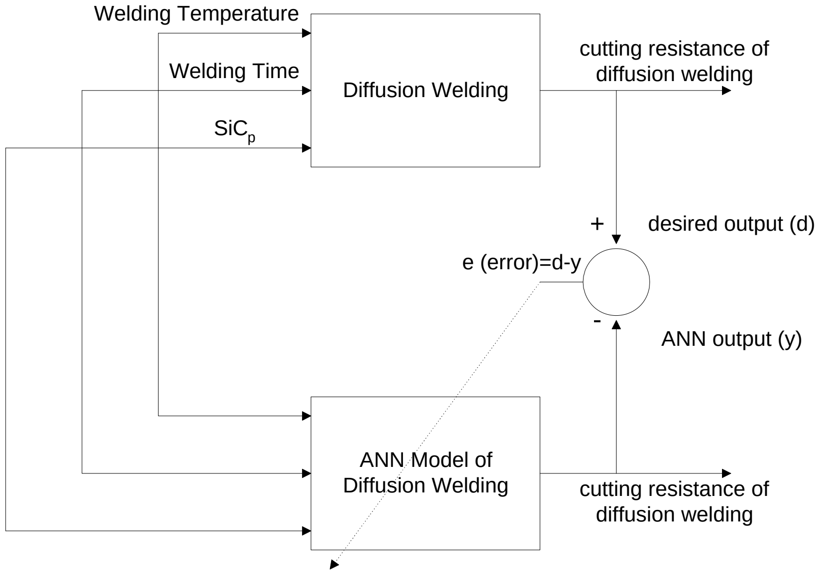

Figure 4. Block diagram of the ANN.

4. RESULTS AND DISCUSION

4.1. Evaluation of bond integrity and parameters

Deformation of surface asperities by plastic flow and creep, grain boundary diffusion of atoms to the voids and grain boundary migration, volume diffusion of atoms to voids can be listed as a sequence of metallurgical stages of the diffusion bonding. Especially with aluminum alloys diffusion bonding can be achieved with adherent surface oxides. In general, the oxide is not removed, but is simply dispersed over a greater surface area in an enclosed environment, in which oxidation cannot recur. At elevated temperatures diffusion mechanism were accelerated and diffusion period were decreased to achieve the same coalescence. Relatively poor coalescence were achieved at 550 ^{0}C process temperatures. Voids were traced at the bond interface. SEM micrographs of weld specimens bonded at 550 ^{0}C process temperatures were presented at Fig.5.

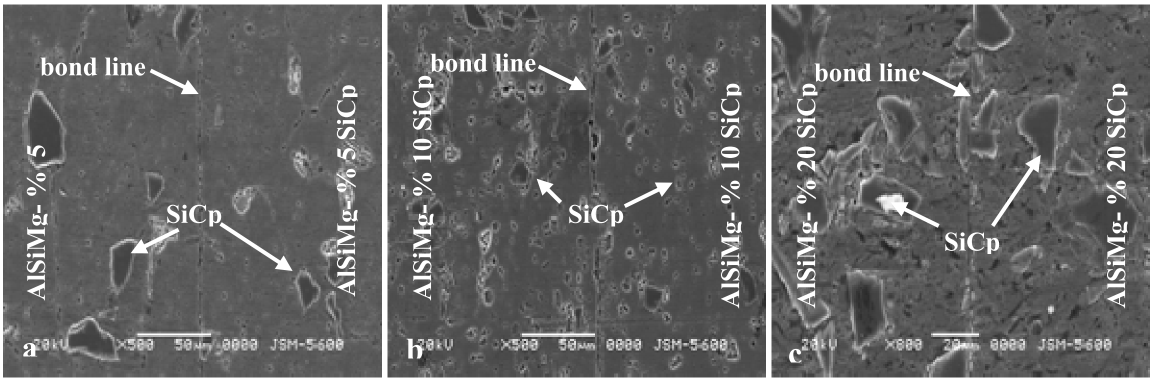

Figure 5. SEM micrograph of specimens bonded at 550 ºC process temperature for 20 minutes.

Reliable coalescence were achieved at weld specimens bonded at 600 ^{0}C. The interface were free of voids and were nearly indistinguishable from parent materials. The mean shear test results were relatively higher than the other process temperatures. SEM micrographs of weld specimens bonded at 600 ^{0}C process temperatures were presented at Fig.6.

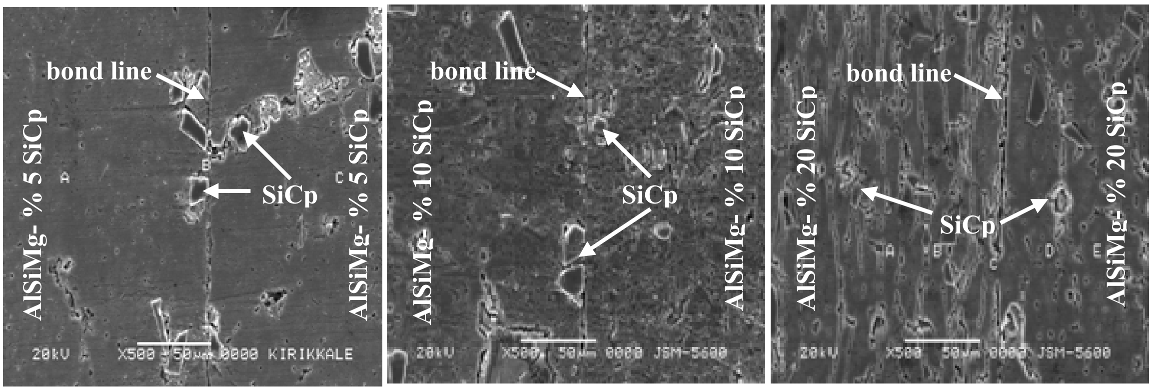

Figure 6. SEM micrograph of specimens bonded at 600 ºC process temperature for 40 minutes.

4.2. ANN approach to shear strength prediction

In this study, prediction of shear strength of diffusion bonded MMC couples were performed by using a back-propagation neural network that uses gradient descent learning algorithm.

a) Bonding process temperature, bonding period and SiC particulate (wt) fractions were used as the model inputs while the shear strength was the output of the model. These datas were obtained from experimental works.

b) Comparison of experimental shear strength test results with predicted values inline with bonding parameters were presented in Table 2. Experimental shear strength of specimen has shown a consistency with predicted results differing 0.01-3. These trained values can lead maximum 5% error in shear strength calculations.

Table 2. Shear strength of predicted values with actual values

Sample No	Couples of samples	Temperatures (°C)	Durations (min.)	Actual values of shear strength (MPa)	Predicted values of shear strength (MPa)	Error (MPa)
1	% **5-5** SiC_p	550	20	56,25	56	+0,25
2	% **5-5** SiC_p	550	40	47	47,34	-0,34
3	% **5-5** SiC_p	550	60	56,33	55,87	+0,46
4	% **5-10** SiC_p	550	20	46,05	46,71	-0,66
5	% **5-10**SiC_p	550	40	55,67	56,28	-0,61
6	% **5-10** SiC_p	550	60	57,78	56	+1,78
7	% **5-20** SiC_p	550	20	48,52	47,73	+0,79
8	% **5-20** SiC_p	550	40	45,90	44,68	+1,22
9	% **5-20** SiC_p	550	60	52,15	52,40	-0,25
10	% **10-10** SiC_p	550	20	45,28	45,10	+0,18
11	% **10-10** SiC_p	550	40	47	46,98	+0,02
12	% **10-10** SiC_p	550	60	46,38	47,38	-1
13	% **10-20** SiC_p	550	20	39,42	40,56	-1,14
14	% **10-20** SiC_p	550	40	30,29	29,77	+0,52
15	% **10-20** SiC_p	550	60	49,77	49,89	-0,12
16	% **20-20** SiC_p	550	20	40,65	39,65	+1

17	% **20-20** SiC_p	550	40	39,80	38,99	+0,81
18	% **20-20** SiC_p	550	60	42,45	42	+0,45
19	% **5-5** SiC_p	575	20	63	61,98	+1,02
20	% **5-5** SiC_p	575	40	66	66,27	-0,27
21	% **5-5** SiC_p.	575	60	73,42	74	-0,58
22	% **5-10** SiC_p	575	20	60	59,66	+0,34
23	% **5-10**SiC_p	575	40	64,92	63,95	+0,97
24	% **5-10** SiC_p	575	60	71,88	70	+1,88
25	% **5-20** SiC_p	575	20	55,10	56	-0,90
26	% **5-20** SiC_p	575	40	62,73	62	+0,73
27	% **5-20** SiC_p	575	60	68	68,03	-0,03
28	% **10-10** SiC_p	575	20	60,20	60	+0,20
29	% **10-10** SiC_p	575	40	65	64,92	+0,08
30	% **10-10** SiC_p	575	60	70,45	71	-0,55
31	% **10-20** SiC_p	575	20	56,99	56	+0,99
32	% **10-20** SiC_p	575	40	62,75	61,25	+1,50
33	% **10-20** SiC_p	575	60	66,62	66,32	+0,40
34	% **20-20** SiC_p	575	20	54,49	54,11	+0,38
35	% **20-20** SiC_p	575	40	58,22	57,15	+1,07
36	% **20-20** SiC_p	575	60	64,56	65	-0,44
37	% **5-5** SiC_p	600	20	71,50	70,69	+0,81
38	% **5-5** SiC_p	600	40	74	73,26	+0,74
39	% **5-5** SiC_p	600	60	85,96	86	-0,04
40	% **5-10** SiC_p	600	20	72,51	71	+1,51
41	% **5-10**SiC_p	600	40	80,08	79,36	+0,72
42	% **5-10** SiC_p	600	60	82,90	83	-0,10
43	% **5-20** SiC_p	600	20	73,64	72	+1,64
44	% **5-20** SiC_p	600	40	75,73	74,52	+1,21
45	% **5-20** SiC_p	600	60	78,18	78	+0,18
46	% **10-10** SiC_p	600	20	66	67,03	-1,03
47	% **10-10** SiC_p	600	40	69,84	68,47	+1,37
48	% **10-10** SiC_p	600	60	76,34	77,14	-0,80
49	% **10-20** SiC_p	600	20	72,16	71,56	+0,60
50	% **10-20** SiC_p	600	40	62,71	61,79	+0,92
51	% **10-20** SiC_p	600	60	73,55	73	+0,55
52	% **20-20** SiC_p	600	20	65	64,80	+0,20
53	% **20-20** SiC_p	600	40	67,92	67,06	+0,86

54	% **20-20** SiC_p	600	60	74,67	73,98	+0,69
55	% **5-5** SiC_p	625	20	72,59	72,09	-0,50
56	% **5-5** SiC_p	625	40	68,28	68	+0,28
57	% **5-5** SiC_p	625	60	59,03	60	-0,97
58	% **5-10** SiC_p	625	20	69,44	70,44	-1
59	% **5-10**SiC_p	625	40	64,19	65	-0,81
60	% **5-10** SiC_p	625	60	57,31	57	+0,31
61	% **5-20** SiC_p	625	20	66	66,62	-0,62
62	% **5-20** SiC_p	625	40	61,94	62,08	-0,14
63	% **5-20** SiC_p	625	60	54	53,40	+0,60
64	% **10-10** SiC_p	625	20	70,76	72,12	-1,36
65	% **10-10** SiC_p	625	40	63,83	63,10	+0,73
66	% **10-10** SiC_p	625	60	56,87	55,97	+0,90
67	% **10-20** SiC_p.	625	20	65,47	64,70	-0,77
68	% **10-20** SiC_p	625	40	59	58,16	+0,84
69	% **10-20** SiC_p	625	60	53,22	52,80	+0,42
70	% **20-20** SiC_p	625	20	60,36	61,37	-1,01
71	% **20-20** SiC_p	625	40	52	51,4	+0,06
72	% **20-20** SiC_p	625	60	50,12	50	+0,12

c) The Sum-squared error (SSE) graphic trained for 5320 Epochs was presented in Fig.7.

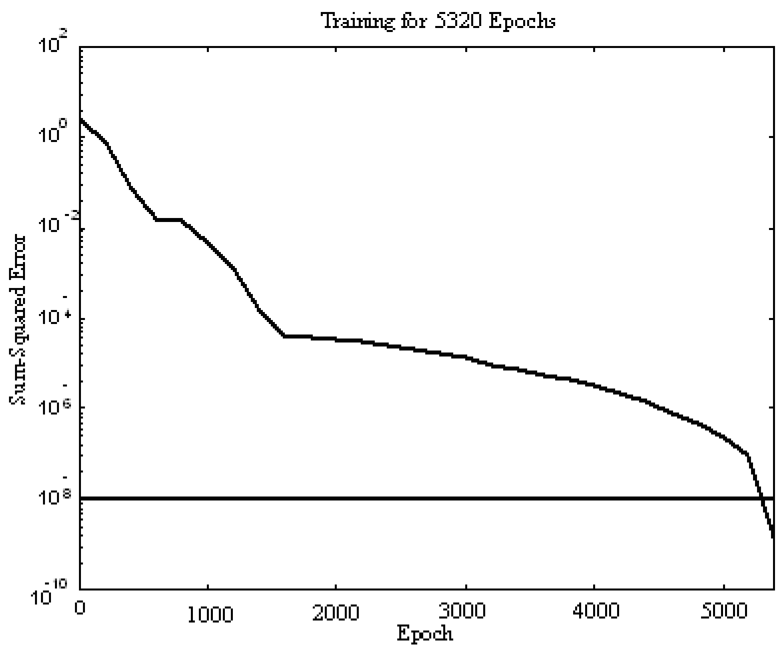

Figure 7. Sum-Squared Error curve versus iteration number.

5. CONCLUSION

The overall performance of the model was quite satisfactory. The low error fractions indicate that ANNs could be a useful tool for modeling and predicting shear strength of bonded interfaces of SiC_p reinforced Al alloy MMCs. Under given conditions, and with prescribed materials predicted shear strength can be utilized by designers and process engineers as and where necessary. Given and predicted values of the ANN system can also be employed at feasibility programs at no cost. This can be handled as a cost saving item at advanced production planning.

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