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Modelling Of Abrasive Wear Resistance By Means Of Artificial Neural Networks Of Al-Sic$_p$ Composıtes Produced By Cold Pressıng Method

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Abstract: In this study, modelling of abrasive wear resistance by means of artificial neural networks of Al-SiC$_p$ composites produced by cold pressing method were obtained using a back-propagation neural network that uses gradient descent learning algorithm. SiC particles with a 32 µm mean diameter were added to the matrix at 5, 10, 15 (wt) % fractions and powders were mixed with 99 % Al. MMC's were fabricated by powder mixing and cold pressing under 400 MPa load and sintering at 400ºC. The wear tests were performed in loads of 2 and 8 N, the abrasive paper 120 and 400 mesh, the wear distance of 20, 40 and 60 m by abrasive test apparatus and the wear losses were calculated. Microstructure examination at wear surface were investigated by optical microscopy, SEM and EDS. Specimens were tested for optical microscopy, SEM, EDS 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 wear distances, different feasible loads and different abrasive paper were used as input, mass loss of abrasive wear specimens at surface 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 modelling of mass loss values of Al/SiC$_p$ metal matrix composite materials processed with abrasive wear method and behavior.

Key words: *Artificial Neural Network, SiC$_p$, MMCs, AbrasiveWear.*

INTRODUCTION

Aluminum-based, particulate-reinforced metal matrix composites (MMCs) are of concerns for structural carrying outs where weight saving is of primary concern. Composites are used not only for their structural properties, such as high shear, tensile strength, modulus of elasticity but also for electrical, thermal, tribological, and environmental applications (Caligulu, U., 2005; Taskin, M., 2000). Researchers are putting much emphasis on the manufacturing, shaping, bonding problems to widespread the use of composites in common industry markets. The process is depended on a number of parameters in particular, the road of wear, feasible loads, lost mass, abrasive sandpaper and surface roughness.

An artificial neural network is a parallel-dispensed information proceduring system. It stores the specimens with dispensed coding, thus forming a trainable nonlinear system. The main idea of neural network draw near to resembles the human brain functioning. Given the inputs and longing outputs, it is also self-adaptive to the habitat so as to respond different inputs rationally (Koker, R., N. Altinkok, 2005). 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 (Altinkok, N., R. Koker, 2005). Artificial Neural networks (ANNs) have been used to model the human vision system. They are biologically inspired and contain a large number of simple processing elements that perform in a manner analogous to the most elementary functions of neurons. Artificial neural networks learn by experience, generalize from previous experiences to new ones, and can make decisions. Neural elements of a human brain have a computing speed of a few milliseconds, whereas the computing speed of electronic circuits is on the order of microseconds. The ANNs are parallel process elements which has characteristic in below.

-ANN is a mathematical model of a biological neuron.

-ANN has very process elements which are related another.

-ANN keeps knowledge with connection weights.

Neural network models provide an alternative approach to implementing enhancement techniques. A simple process element of the NNs is given in Fig.1. Output of i_{th} process element at this simple model is given at Equation 1.

$$y(t+1) = a\left(\sum_{j=1}^{m} w_{ij}\, x_j(t) - \theta_i\right) \tag{1}$$

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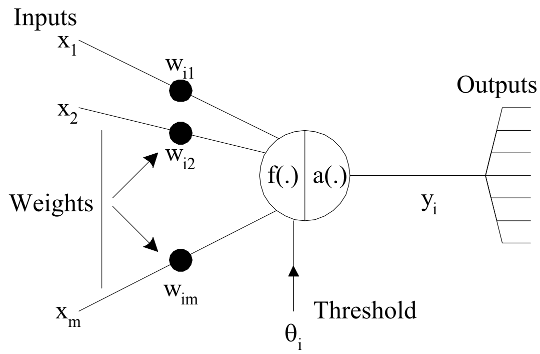


Fig. 1: The mathematical model of neuron

In there, a is activation function, θ_i is threshold value of i_{th} process element. Knowledge processes of process element compose from two parts: input and output. Output of i_{th} process element is calculated with Equation 2 [5-6].

$$f_i \triangleq net_i = \sum_{j=1}^{m} w_{ij} x_j - \theta_i \tag{2}$$

Neural networks were procured a basically different draw near to material modeling and material processing control techniques than statistical or numerical procedures. This method is feasible in many areas of engineering and has produced promising to prepare results in the areas of material modeling and proceduring. One of the main advantages of this approach is that there is no need to make a priori suppositions about material behavior although in more were sophisticated neural network modeling projects one may take advantage of the information of the procedure in network design. Even though multi-layered neural network models cannot make sure a global minimum solution for any given problem, it is a sensible supposition that if the network is trained on a extensive database with a suitable representation project, the resulting model will approximate all of the laws of mechanics that the actual material or process obeys (Chun, M.S., et al., 1999).

Neural networks are essentially connectionist system, in which different nodes called neurons are interconnected. A typical neuron accepts one or more input signals and procures an output signal trusting in the proceduring function of the neuron. This output is conveyed to connected neurons in varying intensities, the signal intensity being decided by the weights. Feed forward networks are jointly used. A feed forward network has a consecutive of layers consisting of a number of neurons in each layer. The output of neurons of one layer come to exists input to neurons of the achieving layer. The first layer, called an input layer, accepts data from the outside world. The last layer is the output layer, which sends knowledge out to users. Layers that lie between the input and output layers are called hidden layers and have no direct touch with the environment. Their presence is needed in order to procure complexity to network architecture for modeling non-linear functional kinship. After choosing the network architecture, the network is tested by using back propagation algorithm, where back propagation algorithm is the productive optimization method used for underrating the error through weight arrangement The trained neural network has to be experimented by supplying testing data (Ganesan, G., et al., 2005; Li, H.J., et al., 2004; Taskin, M., et al., 2008).

The basic fundamentals to build the system model on the basis of NN consist of:

(a) connecting the artificial neurons into a network with respect to certain rules and a topology;

(b) regulating the weights between neurons in term of an proofreading criterion;

(c) establishing the topology and free parameters of the NN by learning specimen data (input patterns) repeatedly;

(d) determining the system model by taking advantage of the strong learning ability of ANN (Fig.2).

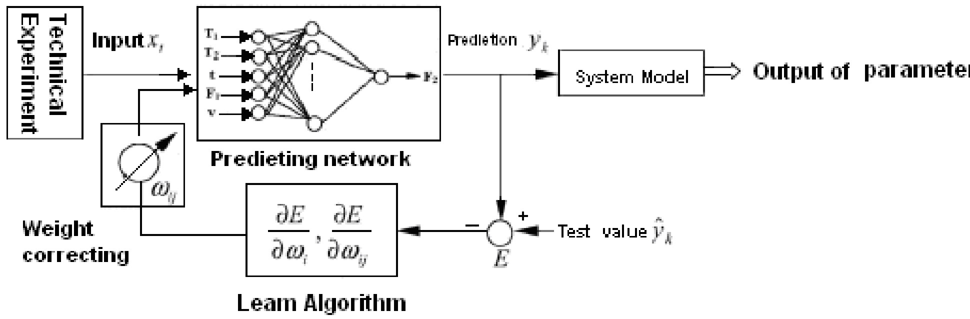


Fig. 2: Scheme of modelling the system by ANN (Chun, M.S., et al., 1999).

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 $[X = x0, x1, \ldots, xn1]^T$

The output vectors $[Y = y0, y1, \ldots, ym1]^T$

where the symbols *n*, *h* and *m* represented the number of neurons in the input layer, the hidden layer and the output layer, sequentially.

2. Materials And Experimental Procedures:

2.1. Fabrication of Al-SiC$_p$ MMCs:

SiC particulate Al alloy MMCs specimens to be produced by cold pressing method were fabricated by powder metallurgy process. SiC particles with a 32 μm mean diameter were added to the matrix at 5, 10, 15 (wt) % fractions and powders were mixed with 99 % Al. Powders were properly mixed with mechanic mixers for homogeneity of the formation. The mixture was cold compacted at 400 MPa in the ϕ12x60 mm steel dies. This is followed by sintering at 400ºC in argon atmosphere for 30 minutes.

2.2. Abrasive Wear Resistance of Al-SiC$_p$ MMC Couples:

Work pieces were prepared for abrasive wearing and surfaces to be weared were protected against corrosion and oxidation. Al alloy MMC specimens with 5-10-15 % SiC (wt) fractions were produced and wearing at abrasive wear apparatus. Schematic illustration of abrasive wear apparatus is given in Fig.3. The wear tests were performed in loads of 2 and 8 N, the wear distance of 20, 40 and 60 m by block on ring test apparatus and the wear losses were calculated. Abrasive paper with 120 and 400 mesh were employed as a wearing agent. Mass loses were measured by a SCALTEC X.10^5 electronic balance with a accuracy.

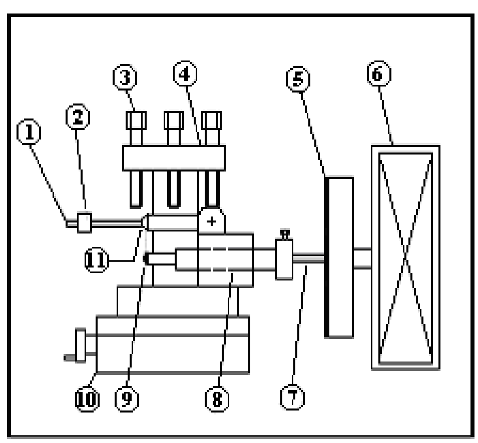


Fig. 3: Schematic illustration of abrasive wear apparatus

1. Load handle, **2.** Load, **3.** Cater screw, **4.** Cater, **5.** Abrasive sandpaper, **6.** Gear box, **7.** Specimen, **8.** Moving specimen conservative, **9.** Bearing, **10.** Spot, **11.** Specimen press handle

2.3. Microstructure Examinations and Adhesive Wear Tests:

After the wearing process, specimens were weighted for mass loss. Grinding of the surface were followed by etching with Keller etchant. Metallographic evaluations and investigations were made by the aid of optical microscopy, SEM and EDS.

Modeling of mass loss values of abrasive wearing behavior at MATLAB program the wear distances, feasible loads, abrasive paper and SiC_p reinforcement (weight) fractions were employed as input and mass loss of specimens of the weared surfaces were recorded as output parameters. Back propagation Multilayer Perceptron (MLP) ANN was used for training of experimental results. ANN modeling the mass loss of the surface of abrasive weared composites was 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		4
The number of neuron on the layers		Input: 4, Hidden: 10, Output: 1
The initial weights and biases		The Nguyen-Widrow method
Activation functions		Log-sigmoid
Training parameters Learning rule		Back-propagation
Adaptive learning rate		Initial: 0.001 Increase: 1.1 Decrease: 0.5
Momentum constant		0.95
Sum-squared error		0.00000001

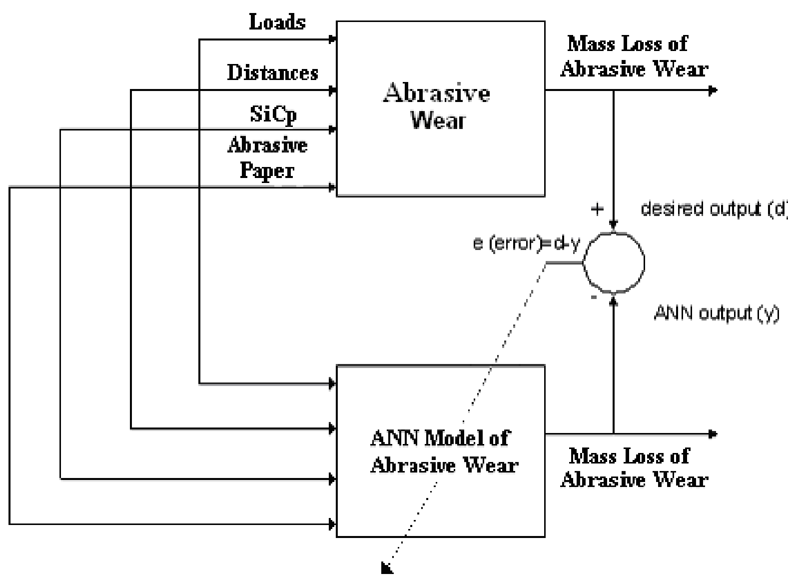


Fig. 4: Block diagram of the ANN.

RESULTS AND DISCUSSION

3.1. Evaluation Of Wear Integrity And Parameters:

Wear tests were performed under various parameters given in related sections. Results of wear and structural data of specimens were evaluated accordingly. Optical micrgraph and SEM of composite specimens namely (a), (b), (c) and (d) were presented in Fig.5. Structural distribution of Al-SiC_p and EDS results of sample (b) were presented in Fig.6. Reinforcing particles were homogenously distributed in the matrix.

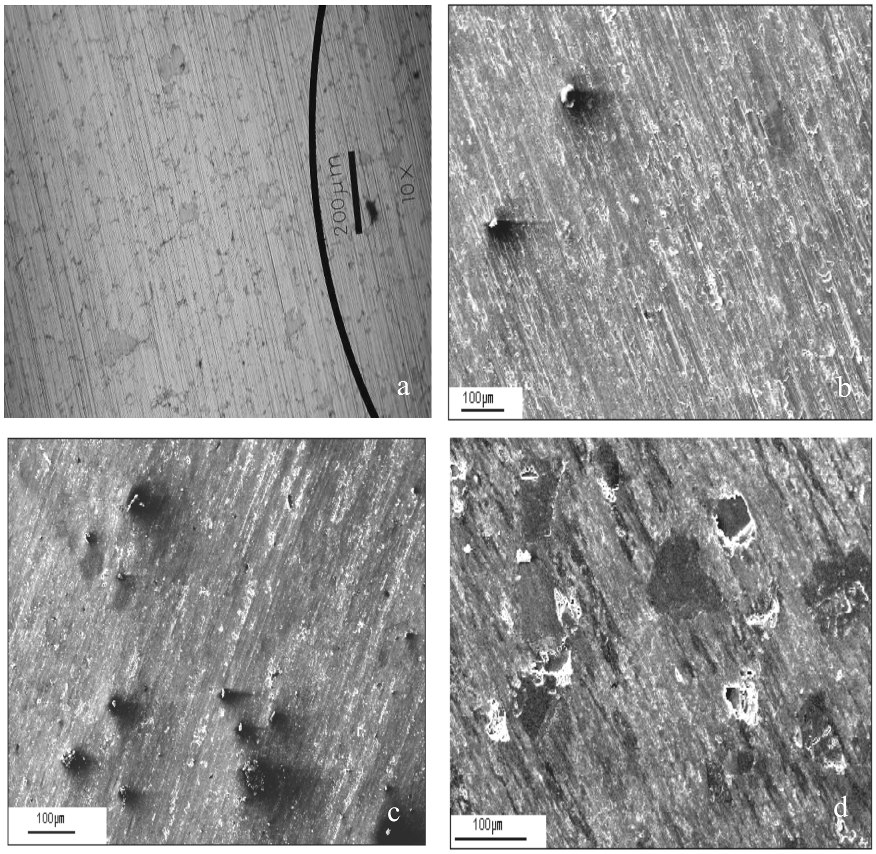


Fig. 5: Micro structures of specimens application process abrasive wear
(a) Al (b) Al-%5 SiC (c) Al-%10 SiC (d) Al-%15 SiC

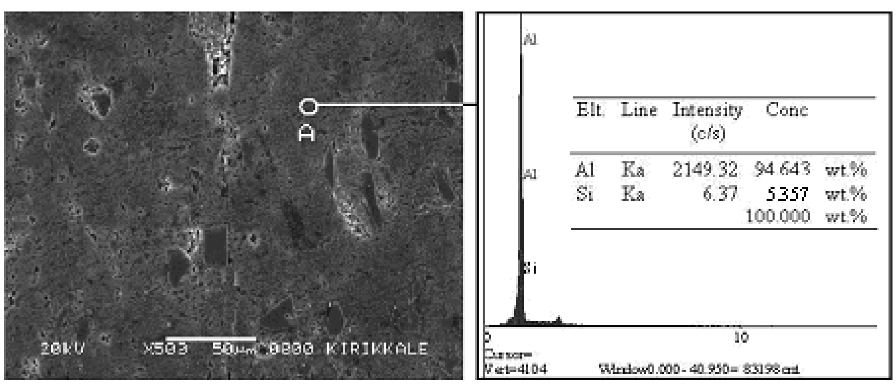
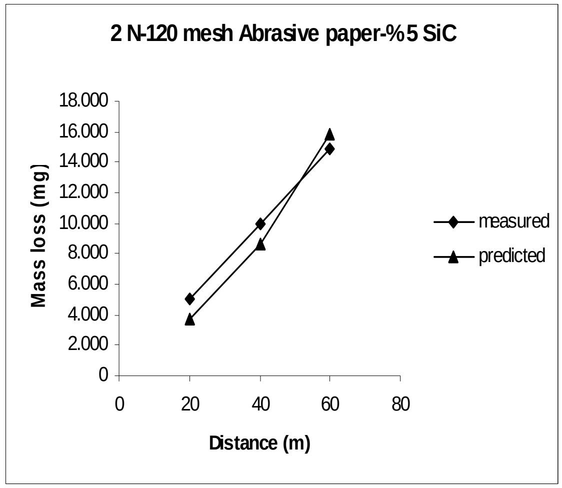
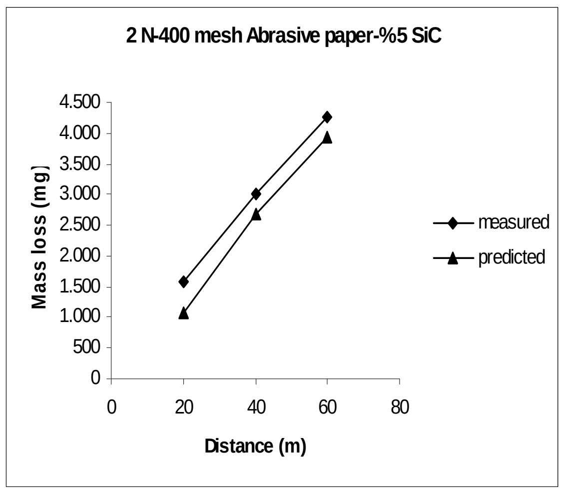
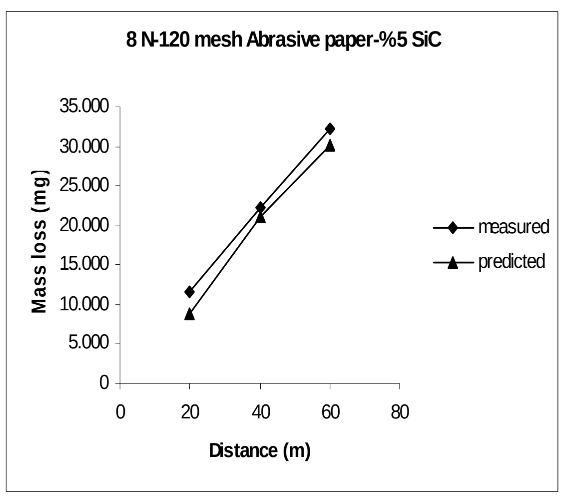


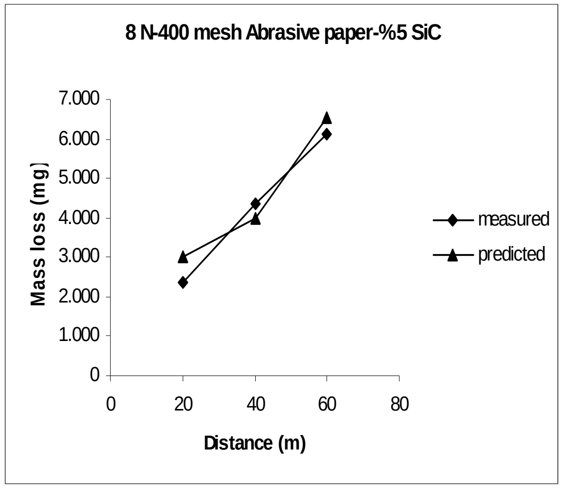
Fig. 6: EDS analysis of specimens (b) weared at %5 SiC

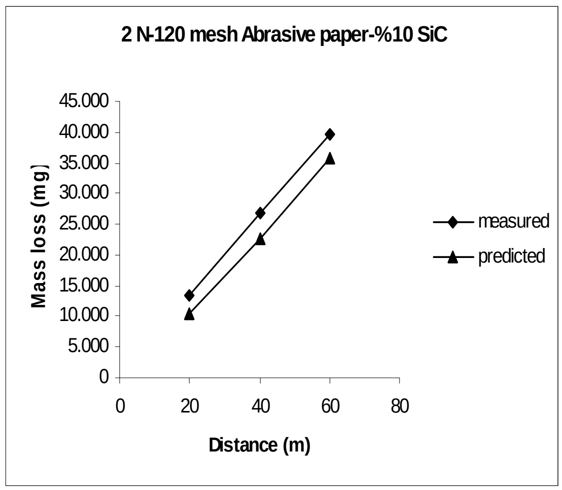
Wear graphic of specimens were presented in Fig.7. Wear loses were increased with the increase of load. Wear loses were decreased while reinforcement fraction of composite were increased.

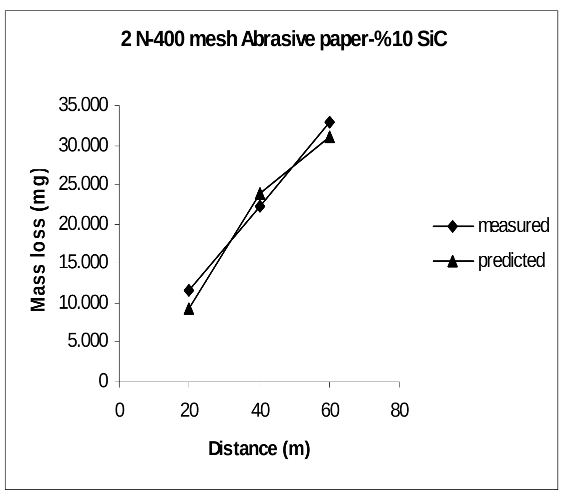

2 N-120 mesh Abrasive paper-%5 SiC
Mass loss (mg)
18.000
16.000
14.000
12.000
10.000
8.000
6.000
4.000
2.000
0
0
20
40
60
80
Distance (m)
measured
predicted

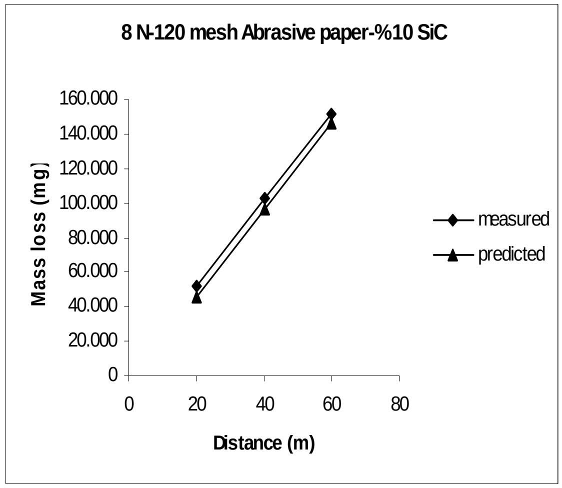

2 N-400 mesh Abrasive paper-%5 SiC
Mass loss (mg)
4.500
4.000
3.500
3.000
2.500
2.000
1.500
1.000
500
0
0
20
40
60
80
Distance (m)
measured
predicted

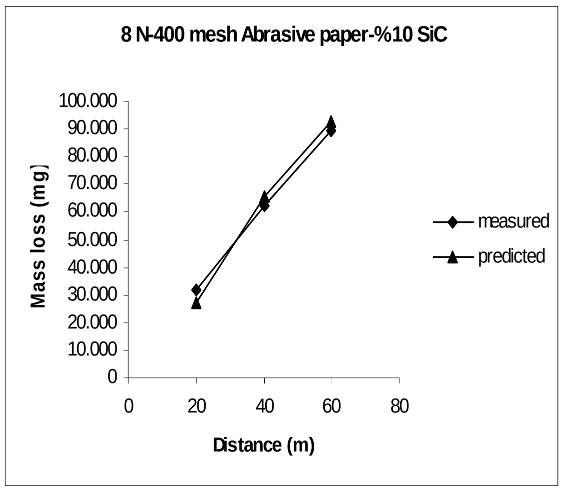

8 N-120 mesh Abrasive paper-%5 SiC
Mass loss (mg)
35.000
30.000
25.000
20.000
15.000
10.000
5.000
0
0
20
40
60
80
Distance (m)
measured
predicted

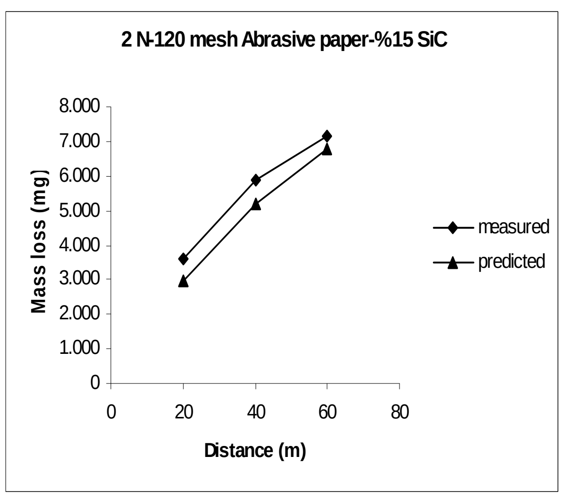

8 N-400 mesh Abrasive paper-%5 SiC
Mass loss (mg)
7.000
6.000
5.000
4.000
3.000
2.000
1.000
0
0
20
40
60
80
Distance (m)
measured
predicted


2 N-120 mesh Abrasive paper-%10 SiC
Mass loss (mg)
45.000
40.000
35.000
30.000
25.000
20.000
15.000
10.000
5.000
0
0
20
40
60
80
Distance (m)
measured
predicted


2 N-400 mesh Abrasive paper-%10 SiC
Mass loss (mg)
35.000
30.000
25.000
20.000
15.000
10.000
5.000
0
0
20
40
60
80
Distance (m)
measured
predicted


8 N-120 mesh Abrasive paper-%10 SiC
Mass loss (mg)
160.000
140.000
120.000
100.000
80.000
60.000
40.000
20.000
0
0
20
40
60
80
Distance (m)
measured
predicted


8 N-400 mesh Abrasive paper-%10 SiC
Mass loss (mg)
100.000
90.000
80.000
70.000
60.000
50.000
40.000
30.000
20.000
10.000
0
0
20
40
60
80
Distance (m)
measured
predicted


2 N-120 mesh Abrasive paper-%15 SiC
Mass loss (mg)
8.000
7.000
6.000
5.000
4.000
3.000
2.000
1.000
0
0
20
40
60
80
Distance (m)
measured
predicted

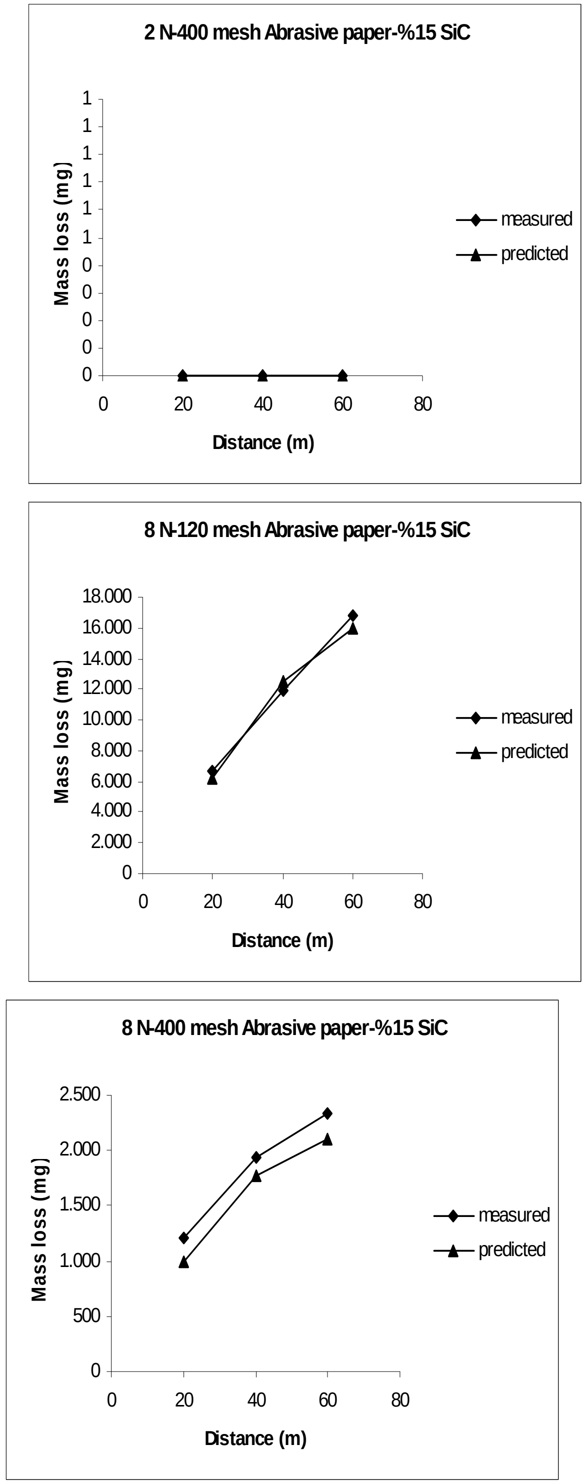


Fig. 7: Abrasive graphics of composites

3.2. ANN Approach to Lost Mass Prediction:

In this study, predictions of mass loss of abrasive wear MMC couples were performed by using a back-propagation neural network that uses gradient descent learning algorithm.

a) Wear distances, feasible load, abrasive paper and SiC particulate (wt) fractions were used as the model inputs while the mass loss was the output of the model. These datas were obtained from experimental works.

b) Comparison of experimental abrasive wear test results with predicted values inline with wearing parameters were presented in Table 2. and dimensional test results were presented Fig. 8. Experimental mass losses of specimens have shown a consistency with predicted results differing 0.01-5. These trained values can lead maximum 10 % error in mass loss calculations.

c) The Sum-squared error (SSE) graphic trained for 5800 Epochs was presented in Fig.8.

Table 2: Abrasive wear resistance of predicted values with actual values

Sample No	MMC_s samples	Loads (N)	Abrasive paper (Mesh)	Distances (m)	Actual values of mass loss (mg)	Predicted values of mass loss (mg)	Error (MPa)	% Error
1	Al-%5SiC_p	2	120	20	5.051	3.700	+1.351	+26.74
2	Al-%5SiC_p	2	120	40	10.017	8.600	+1.417	+14.14
3	Al-%5SiC_p	2	120	60	14.911	15.867	-0.956	-6.41
4	Al-%5SiC_p	8	400	20	1.571	1.068	+0.503	+32.01
5	Al-%5SiC_p	8	400	40	3.008	2.674	+0.334	+11.10
6	Al-%5SiC_p	8	400	60	4.265	3.921	+0.344	+8.06
7	Al-%5SiC_p	2	120	20	11.505	8.800	+2.705	+23.51
8	Al-%5SiC_p	2	120	40	22.224	21.000	-1.224	-5.50
9	Al-%5SiC_p	2	120	60	32.325	30.100	+2.225	+6.88
10	Al-%5SiC_p	8	400	20	2.385	3.010	-0.625	-26.20
11	Al-%5SiC_p	8	400	40	4.377	3.988	+0.389	+8.88
12	Al-%5SiC_p	8	400	60	6.137	6.545	-0.408	-6.64
13	Al-%10SiC_p	2	120	20	13.558	12.980	+0.578	+4.26
14	Al-%10SiC_p	2	120	40	26.702	26.172	+0.53	+1.98
15	Al-%10SiC_p	2	120	60	39.568	41.100	-1.532	-3.87
16	Al-%10SiC_p	8	400	20	11.483	9.300	+2.183	+19.01
17	Al-%10SiC_p	8	400	40	22.330	23.900	-1.57	-7.03
18	Al-%10SiC_p	8	400	60	32.844	31.000	+1.844	+5.61
19	Al-%10SiC_p	2	120	20	51.560	46.000	+5.560	+10.78
20	Al-%10SiC_p	2	120	40	102.296	96.000	+6.296	+6.15
21	Al-%10SiC_p	2	120	60	151.300	146.000	+5.300	+3.50
22	Al-%10SiC_p	8	400	20	32.014	27.200	+4.814	+15.03
23	Al-%10SiC_p	8	400	40	62.424	65.600	-3.176	-5.08
24	Al-%10SiC_p	8	400	60	89.623	92.700	-3.077	-3.43
25	Al-%15SiC_p	2	120	20	3.586	2.946	+0.64	+17.84
26	Al-%15SiC_p	2	120	40	5.865	5.173	+0.692	+11.79
27	Al-%15SiC_p	2	120	60	7.163	6.800	+0.363	+5.06
28	Al-%15SiC_p	8	400	20	0.346	0.425	-0.079	-22.83
29	Al-%15SiC_p	8	400	40	0.591	0.448	+0.143	+24.19
30	Al-%15SiC_p	8	400	60	0.793	0.729	+0.064	+8.07
31	Al-%15SiC_p	2	120	20	6.664	6.215	+0.449	+6.73
32	Al-%15SiC_p	2	120	40	11.973	12.460	-0.667	-5.57
33	Al-%15SiC_p	2	120	60	16.791	15.972	+0.819	+4.87
34	Al-%15SiC_p	8	400	20	1.212	1.000	+0.212	+17.49
35	Al-%15SiC_p	8	400	40	1.933	1.765	+0.168	+8.69
36	Al-%15SiC_p	8	400	60	2.336	2.108	+0.228	+9.76

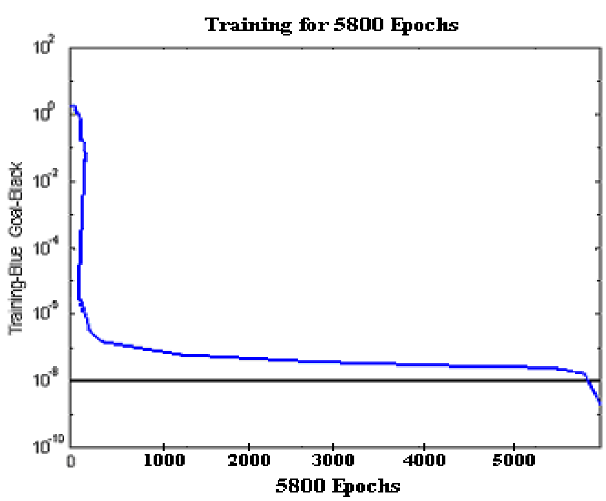


Fig. 8: Sum-Squared Error curve versus iteration number.

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 mass loss of abrasive weared surfaces of SiC_p reinforced Al alloy MMCs. Under given conditions, and with prescribed materials predicted mass loss 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.

REFERENCES

Altinkok, N., R. Koker, 2005. "Neural Network Approach to Prediction of Bending Strength and Hardening Behaviour of Particulate Reinforced (Al–Si–Mg)-Aluminium Matrix Composites", Materials and Design, 25, 595-602.

Avci, E., I. Turkoglu and M. Poyraz, 2005. "Intelligent Target Recognition on Based Wavelet Packet Neural Network", Elsevier Expert Systems with Applications, 29: 175-182.

Avci, E., I. Turkoglu and M. Poyraz, 2005. "Intelligent Target Recognition Based on Wavelet Adaptive Network Based Fuzzy Inference System", Lecture Notes in Computer Science, Springer-Verlag, 3522 / 2005, pp: 594-601.

Caligulu, U., 2005. "The Investigation of Joinability of Diffusion Bonding with Hot Pressing Manifactured AlSiMg-SiC_p Reinforced Composites", Fırat Uni. Graduate School of Naturel and Applied Sciences Department of Metallurgy Education, Master Thesis, Elazig.

Chun, M.S., J. Biglou, J.G. Lenard and J.G. Kim, 1999. "Using Neural Networks to Predict Parameters in The Hot Working of Aluminum Alloys" Journal of Materials Processing Technology, 86245-251.

Ganesan, G., K. Raghukandan, R. Karthikeyan and B.C. Pai, 2005. "Development of Processing Map for 6061 Al/15% SiCp Through Neural Networks", Journal of Materials Processing Technology, 166: 423-429.

Koker, R., N. Altinkok, 2005. "Modelling of The Prediction of Tensile and Density Properties in Particle Reinforced Metal Matrix Composites by Using Neural Networks", Materials and Design, p: 1-7.

Li, H.J., L.H. Qi, H.M. Han and L.J. Guo, 2004. "Neural Network Modeling and Optimization of Semi-Solid Extrusion for Aluminum Matrix Composites", Journal of Materials Processing Technology, 151: 126-132.

Taskin, M., 2000. "Diffusion bonding of fine grained high carbon steels in the superplasticity temperature range", Fırat University Graduate School of Naturel and Applied Sciences Department of Metallurgy Education, Doctora Thesis, Elazig.

Taskin, M., U. Caligulu, A.K. Gur, 2008. "Modeling Adhesive Wear Resistance of Al-Si-Mg-/SiCp PM Compacts Fabricated by Hot Pressing Process, By Means of ANN" Int J Adv Manuf Technol., 37: 715-721.