MASS LOSS PREDICTION OF NEWLY DEVELOPED ALUMINIUM-BASED ALLOYS USING ARTIFICIAL NEURAL NETWORK

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Abstract: The purpose of this study is to predict the mass loss of newly developed aluminium based alloy. Two different alloys are prepared by cladding process and the sliding friction and wear properties of this alloy against high carbon high chromium steel are investigated at different normal loads (50 N, 60 N and 70 N) under different sliding distances. Tests are carried at a constant speed of 1 m/sec under oil lubricated conditions by preheating the circulating engine oil 20w40 at a temperature of 80^0C. The mass losses are measured and recorded for every interval. An artificial neural network (ANN) model is developed to predict the mass loss of newly developed aluminium-based alloy. It is observed that the predicted values have shown good agreement with experimental values with a correlation coefficient of 0.999973. This model can also be used to predict the mass loss of any material.

Key words: *Mass loss, aluminium-based alloy, sliding wear, ANN*

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1. Introduction

Aluminium alloys and other lightweight materials have emergent applications in the automotive industry, with respect to reducing the fuel consumption and shielding the environment, where they can successfully put back steel and cast iron parts. These alloys are widely used in buildings and constructions, containers and packaging, marine, aviation, aerospace and electrical industries because of their lightweights, corrosion resistance in most environments or combination of these properties [1]. Aluminum alloys have higher conductivities (electrical and thermal) than most other metals, and they are usually cheaper than the alloys that are superior conductors (copper, silver, gold, and so on) [2]. Aluminium based alloy provides good combination of strength, corrosion resistance, together with fluidity and freedom from hot shortness [3].

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The additions of Sn or Si with Al-based alloys are commonly used in plain bearings and internal combustion engine components [4-5] because of their fine tribological and mechanical properties. The addition of Sn will improve the anti-frictional characteristic as well as decrease the coefficient of friction [6-7]. Likewise addition of Si will exhibit excellent wear resistance [8], but it has poor seizure resistance under poor lubricating conditions, particularly during starting or warming up of engines. This problem can be overcome by addition of Si in Al-Sn alloys and this combination of the alloy will be able to support heavy loads, resistance to seizure gets improved [9] and also improves the corrosion resistance [10]. The increase of Sn and Si content in Al-based alloys will decrease the wear rate, and the friction factor decreases hardly varies with increase in Si content while slightly with increase in Sn content [11]. So, the Al-based alloys are used in most of the structural components, predominantly in bearing applications in which the wear property is of considerable importance.

Durmus have used ANN to predict wear loss and surface roughness of AA6351 aluminium alloy, at various aging temperatures, load, sliding speed and abrasive grit diameter. It was shown that the experimental results coincide with ANN results [12]. Taskin have modelled adhesive wear resistance of Al-Si-Mg-/SiCp MMC compacts which fabricated by powder metallurgy hot pressing process at different reinforcement fractions (5-10-15% SiCp), loads and wear resistance [13]. Microhardness values of Al/SiCp metal matrix composite material processed with diffusion method was investigated by Taskin [14]. Cetinal et al have developed the Mo coatings in ductile iron substrate using the atmospheric plasma-spray system. The mass loss of this substrate was measured by pin-on-plate type friction/wear test equipment, which was subjected to slide against the AISI 303 steel under dry and acid environments at different loading conditions. The results obtained from trained neural network model and the experimental results were found to be reasonably close [15].

The prediction of mass loss of A390 aluminium alloy using feed-forward back propagation neural network at different loads, sliding speed and time was done by John Presin Kumar [16] and the same algorithm was used to build a model to predict the material removal rate in machining of Al/SiC_p which had shown a good agreement with the experimental values [17]. The abrasive wear characteristics of sintered steels containing Molybdenum di Sulphide powders sliding against SiC abrasive sheet at room temperature was predicted by using ANN [18]. The wear loss of aged 2024 and 6063 aluminium alloys were predicted by using back-propagation ANN approach at different aging temperature, aging time and applied load. In this model 2 hidden layers and 4 neurons in hidden layers were used. The overall performance was satisfactory and the result showed that ANN could be considered an alternative to practical technique and for no experimental cost [19].

The mechanical property of Al-Si-Cu alloy was predicted using neural network with different chemical compositions and cooling rate. The result showed good compatibility with experimental data and accuracy is much higher than using the classical, experimental models [20]. The prediction of tool wear used in universal milling machine is an important role in industry for higher productivity and product quality. The use of feed forward back propagation neural network, the flank wear at different cutting speed, feed, depth of cut were found to be capable of better predictions within the trained range [21]. The computer neural networks have introduced to predict the tribological properties of a given material/mechanical system in order to reduce the amount of experimental test. In this study, experimental and ANNs results have been compared [22].

All the above researches show that the ANN is a meaningful technique in modeling. Hence in the present work, an attempt is made to develop an ANN model to predict the mass loss of the newly developed alloy. Based on the experimental records, optimized and trained neural networks are used to predict the mass loss.

2. Material Preparation and Testing

2.1 Alloy Preparation and Its Chemical Composition

In this work, Aluminium-based alloys are prepared by cladding process. This is the most popular method to avoid the adverse effect of tin with a bonding layer of pure aluminum before steel backing. The continuously cast strip of aluminium bearing alloy together with a strip of low carbon steel is achieved by cold rolling [23-24]. Fig. 1-2 show the different layers used in aluminium-based alloy.

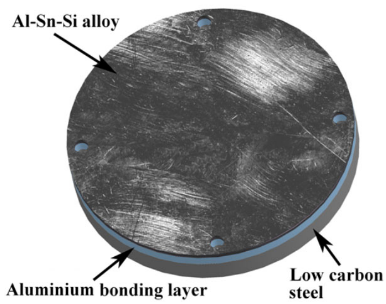

Fig. 1 *Layer of alloy 1.*

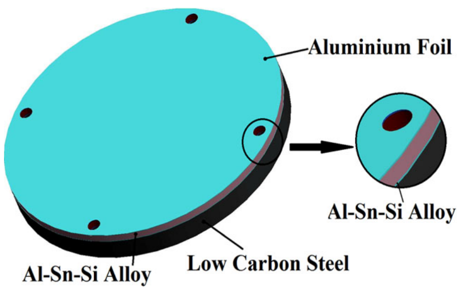

Fig. 2 *Layer of alloy 2 (heat treated).*

The second specimen prepared is subjected to heat treatment (T6) with the following conditions: solutioning at 548^0C for 8 hour, water quenching and artificial aging at 160 ± 5^0C for 6 hour. The lining thickness of the alloys is measured by using permascope. The chemical composition and the lining thickness of newly-developed alloy and pin are referred in Tab. I.

2.2 Friction and Wear Tests

Wear tests were carried out on the pin-on-disc tribometer under lubricating sliding conditions (Fig. 3). The pin material used in this study is prepared with shaft material of AISI D3 (High Carbon High Chromium Steel) having a diameter of 5.041 mm and hardness 720 BHN, and the disc with newly developed alloy having a dimension of 100 mm diameter and 15 mm thickness. The normal load to the pin can be varied from 196 to 1962 N and the disc speed can be varied from 100 to 1200 rpm.

	Chemical Composition	Lining thickness, μm
Pin	2-2.5 % C 0.25-0.3 % Mn 0.25-0.3 % Si 0.2 % V 0.8 % Mo Fe remaining	–
Alloy 1	9.0-12.5% Sn 0.8-1.25% Cu 2.7-3.35% max Si Al rest of composition	575
Alloy 2	7.5-12 % Sn 1.25-1.65 % Cu 2.25-2.85 Si Al rest of composition	425

Tab. I *Composition and Lining thickness of Pin and Alloy.*

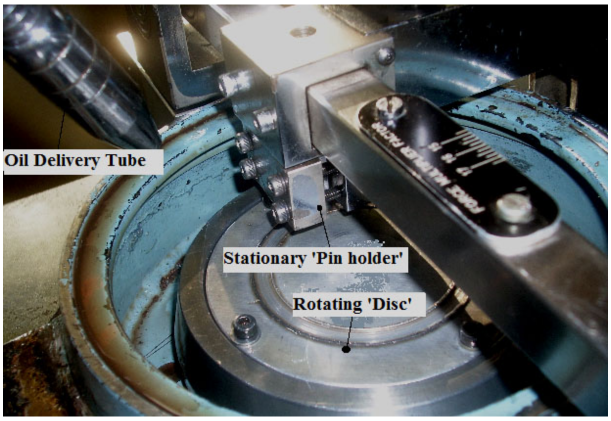

Fig. 3 *Pin-on-disc tribometer.*

The following test conditions are followed in the investigation:

Sliding speed (m/s) – 1
Track diameter (mm) – 75
Normal load (N) – 50, 60, 70
Oil temperature (^{0}C) – 80
Lubrication method – Dropping oil onto the revolving disc

The disc is driven by an electric motor and the wear tests are performed under different normal loads and for various sliding distances of 9 km, 18 km, 27 km, 36 km, 45 km and 54 km. The tests are replicated at least three times for each experimental condition. During the test, the wear is measured through an LVDT

(Linear Variable Displacement Transducer)_and digital displacement monitor. The tangential frictional force is measured continuously through a 20 kg load cell and a digital load indicator and also the readings are recorded for every 10 minutes. The value of friction coefficient is calculated from the equation (1)

$$\text{Friction coefficient} = \frac{\text{Friction Force}}{\text{Applied Load}} \tag{1}$$

The mean value of the friction coefficient is determined. At the end of each test, the experiment is stopped, the disc is removed and the mass loss is measured using electronic precision balance having 0.1 mg sensitivity. These mass losses of the alloy are used to study the effect of load and sliding distance on the wear resistance of the alloy against shaft material. Finally, the worn surfaces of the alloy are examined with SEM.

3. Modeling Using Artificial Neural Network

The neural networks can be used with many complicated functions, because of their sophisticated nature. This technique brings out in almost every technological field to solve ample range of problems in convenient and in an easier way [25-26]. Owing to natural self-learning nature of neural networks, their activities can be sometimes unpredictable and unexpected.

It has similar structure of brain cells of human neural networks and is interconnected with each other. The performance of the ANN model is evaluated by separating the data into two sets: the training set and the testing set. During the training set, the parameters of the network are calculated. Then the learning process is stopped when the error goal is reached and finally the network is evaluated with the data from the testing set. It consists of large number of simple synchronous processing elements called neurons, and is assembled in different layers in the network such as an input layer, an output layer and hidden layers as shown in Fig. 4.

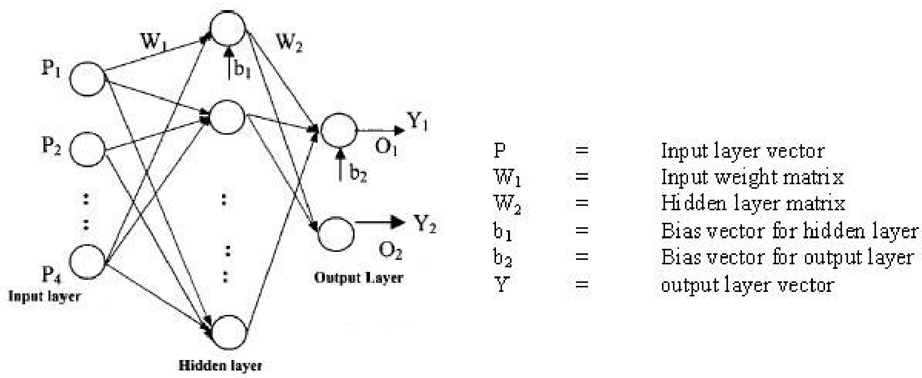

Fig. 4 *Feed-forward neural network architecture.*

The input layer receives input from external environment and the output layer that communicate the output of the system to the user or external environment. There are usually a number of hidden layers between these two layers. The process continues until the network outputs fit the targets. Once the network is trained, the neural network may be used to calculate the output for any arbitrary set of input data through the fixed weight factors and the errors are also calculated. Finally, normalized Root Mean Square Error value (RMSE) is used to evaluate the training performance of the ANN.

ANN has the potential to minimize the need for expensive experimental investigation and/or inspection of aluminum alloys used in various applications, hence resulting in large economic benefits for organizations. The training phase can be finished in few minutes whereas the experimental study lasts for a number of days.

In the present work, the neural network models are designed and trained using the MATLAB 7.5.0.342 package. Back propagation algorithm is used for predicting the mass loss under lubricated conditions. The input selection is a very important aspect of neural network modelling [27]. In this work, the network has three neurons in input layer (load, sliding distance and different alloying element), one neuron in output layer (mass loss) and 15 neurons in each hidden layer is used. So the architecture of ANN is 3:15:15:1 as shown in Fig. 5.

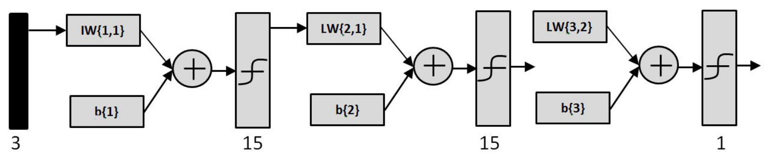

Fig. 5 *ANN Architecture for this study.*

The network has constructed using 36 experimental data, among those 28 data are used for training process and the remaining data for testing process. All the input and output values are normalized between 0.1 and 0.9 by using linear scaling. Sigmoid activation function is selected as the transfer function and learning rate and momentum are set as 0.8 and 0.8 respectively.

In the learning stage the mean errors are 0.175% and 0.151% for the alloy 1 and 2 respectively. The training process is ended after 15000 epochs. Fig. 6 shows the Normalized Standard Error (NSE) with training cycles which decreases with increasing number of iteration and attains 3.01578e-005. The testing process is carried out, in order to understand whether the ANN is making good predictions. The mean errors in the testing stage are found to be 6.911% for alloy 1 and 7.498% for alloy 2.

4. Results and Discussion

4.1 Microstructural Analysis and Wear Tests

Metallographic samples are polished according to standard techniques and etching and the microstructure of the alloy is obtained using Scanning Electron Microscope

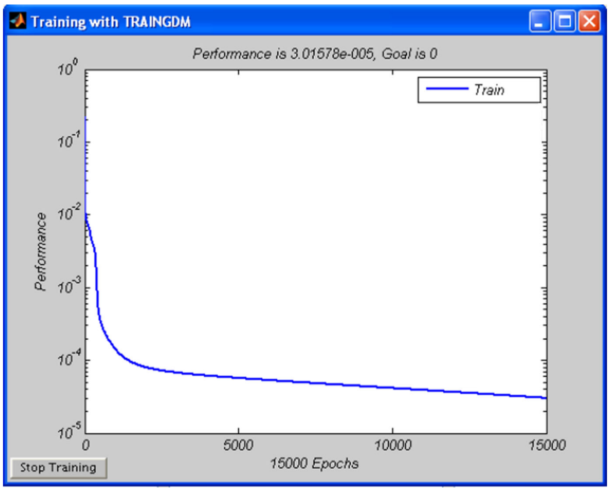

Fig. 6 *ANN training performance graph.*

(SEM). Fig. 7-8 shows the microstructure of newly developed aluminium-based alloy and was investigated using SEM. In both the cases, alloy consists of black α (Al) phase and white reticulate phase β (Sn) which is uniformly distributed. The black phase in the matrix is Sn, and phases surrounded with Sn are Si. The eutectic Si phase appears as needle-like structure and this 'peritectic-type' islands microstructure is the most advantageous to anti-friction characteristics and wear resistance properties [28].

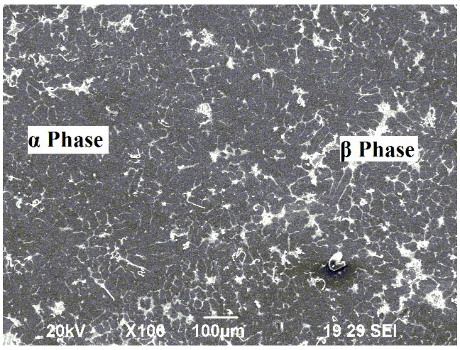

Fig. 7 *Microstructure for alloy 1.*

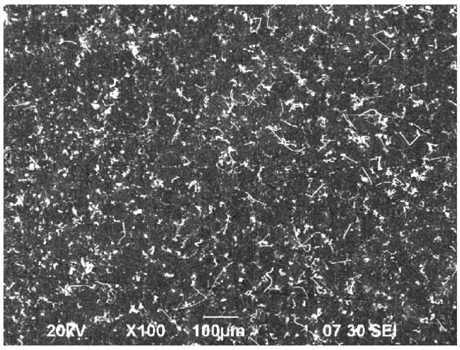

Fig. 8 *Microstructure for alloy 2.*

Relations of sliding distance versus mass loss are presented in fig. 9-10 and wear curves are obtained in tests for varying applied load is 50, 60, and 70 N with a sliding speed of 1 m/s. Due to impact load, the initial wear is greater and the reason for higher initial wear is that the static friction is higher than dynamic friction [29]. Later the wear gradually increases, but comparatively very less than initial wear.

The asperities of the alloy (disc) is in contact with the asperities of pin material, and then the shape of asperities gets changed. Initially the upper layer of asperities will be rough, while in continuing the sliding rough surface turns into relatively smooth surface. Finally the wear is less compared to previous sliding distance. This indicates that the surface of asperities gets smoothened and relatively low frictional force results due to which the wear becomes insignificant [29-30].

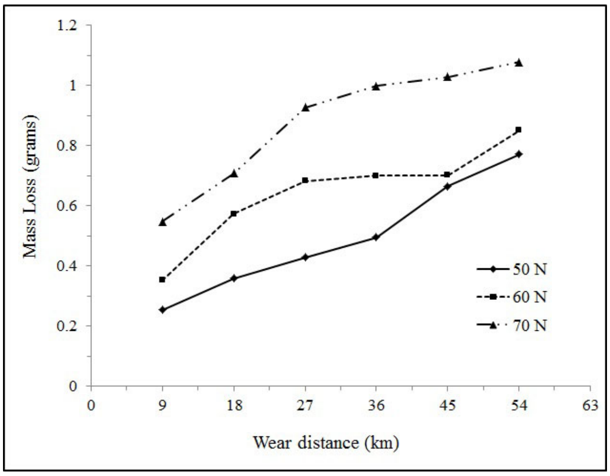

Fig. 9 *Wear graph for alloy 1.*

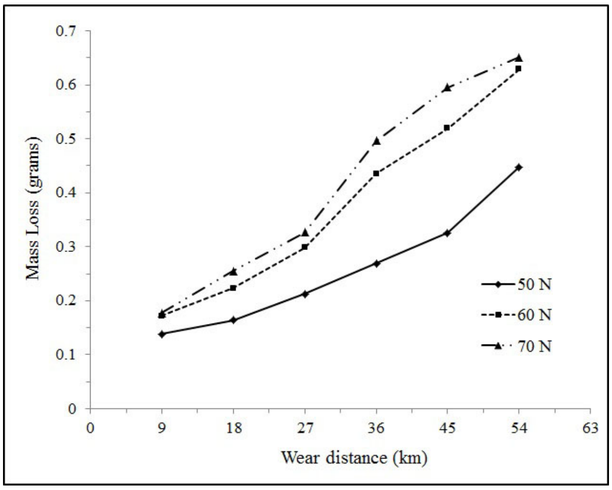

Fig. 10 *Wear graph for alloy 2.*

4.2 Wear Surface Examinations

The worn surfaces of the discs are examined using the Scanning Electron Microscope (SEM). The worn surfaces of the newly developed alloys after the wear tests are presented in fig. 11-12. Worn surface of Fig. 11(a-b) is not even, when compared to the worn surface of Fig. 11(c). In other words, not greatly distension and extensive deep wear appeared on the wear surface of Fig. 11(a-b). Some deep pits, grooves and continuous scratches are observed on the wear surfaces. These grooves and scratches resulted from the ploughing action of asperities on the alloy surface. Hard debris originating from fragmented and oxidized asperities of alloy and abraded surface of steel disc gets entrapped in between the contacting surfaces and behaves as a cutting tool causing abrasion. With increase applied normal load, more deformation of worn surface is shown in Fig. 11(c). As the load increase, the wear behaviour of alloy changes from abrasion to delamination [8] as evident from the SEM micrographs.

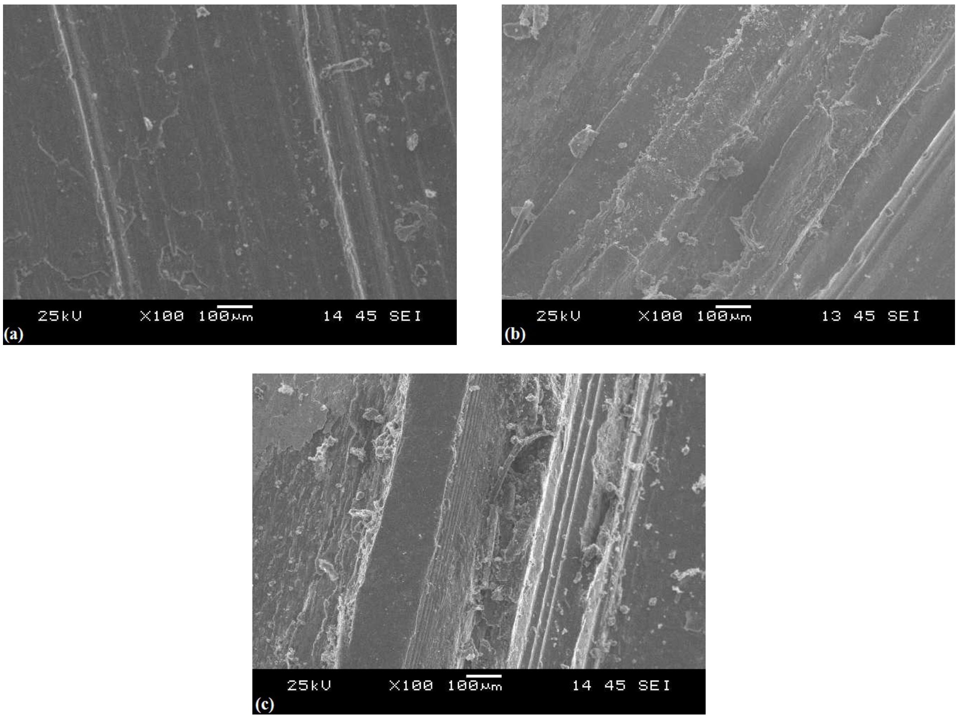

Fig. 11 *Wear surface of alloy 1 under the load of (a) 50 N (b) 60 N (c) 70 N.*

In the second alloy, when the load is increased (Fig. 12(c)), the worn surfaces of the alloys are appeared not smooth (even) and also deeper wear grooves, because of higher temperature rise, and the surface of the alloys gets soften and swell more easily. It also confirmed many of serration marks and entrapped wear debris. The greater quantity of material flow over the worn surface is the impact of serration marks and the occurrence of wear debris caused by fracture. But the same damage

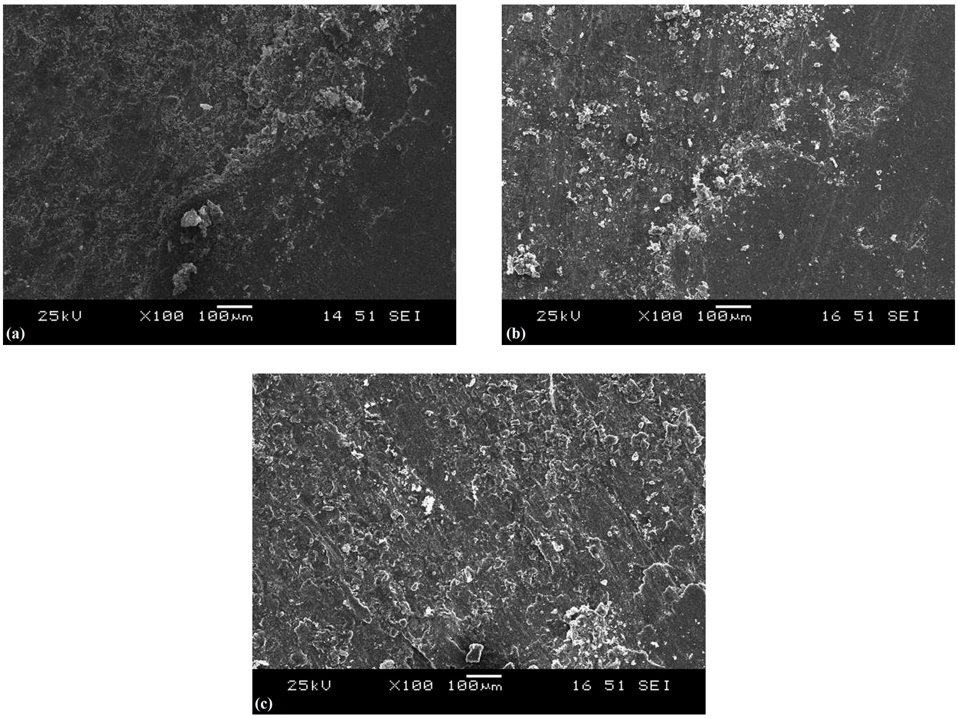

Fig. 12 *Wear surface of alloy 2 under the load of (a) 50 N (b) 60 N (c) 70 N.*

is not occurred on the lower normal load 60 N and especially at 50 N (Fig. 12(a-b)), but also observed that the some pits/caves on the wear surfaces of the alloys.

4.3 Statistical Analysis of ANN Model

The statistical methods of Root Mean Square Error (RMSE), Mean Percentage Error (MPE), Absolute Percentage Error (APE), and Absolute Fraction of Variance values have been used for making comparisons. The above values can be evaluated by the following equations 2-5 [31-32]:

$$\text{RMSE} = \left(\frac{1}{n}\sum\nolimits_j \left|a_j - p_j\right|^2\right)^{\frac{1}{2}} \tag{2}$$

$$\text{MPE} = \left(\frac{\sum_j \left(\left(a_j - p_j\right)/a_j\right)}{n}\right) \times 100 \tag{3}$$

$$\text{APE}\ (\%) = \left|\frac{\text{Model prediction values} - \text{Experimental values}}{\text{Experimental values}}\right| \times 100 \tag{4}$$

$$R^2 = 1 - \left(\frac{\sum_j (a_j - p_j)^2}{\sum_j (p_j)^2} \right) \tag{5}$$

where p is the predicted value, a is the experimental value, j is the processing elements and n is the number of samples. Statistical values between the network predictions and the experimental values using training and testing process have been shown in Tab. II.

	Training performance	Testing performance
RMS	0.00019039	0.00659707
R^2	0.99998609	0.99267766
MPE	-0.000876	0.125696

Tab. II *Statistical values of the mass loss of the newly developed alloys.*

The experimental values are compared with the predicted values, so that the performance of the trained network is tested and the results are as shown in Fig. 11-12.

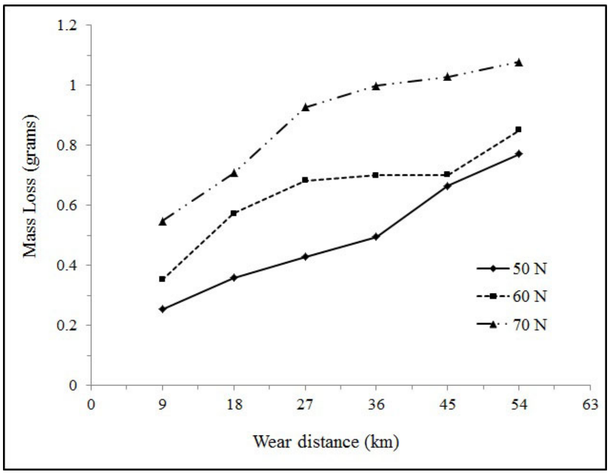

Fig. 13 *Comparison of mass loss at training stage.*

The values are within acceptable ranges which meets the reliability of the ANN training and testing stages and the summary of the proposed model (Fig. 9) is given in Tab. III.

Very good performance of the trained neural network is attained and the predictions are in good concord with the experimental values.

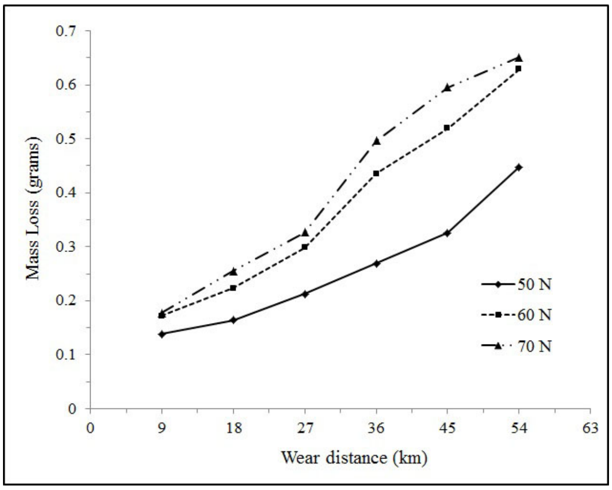

Fig. 14 *Comparison of mass loss at testing stage.*

Parameters used in ANN model	
Object model	Mass loss prediction
The number of layers	4
Number of hidden layers	2
The number of neuron on the layers	Input: 3; hidden1: 15; hidden2: 15; output: 1
Network type	Feed-forward back propagation
Transfer function	Log-sigmoid
Training function	Trainlm
Learning function	Learngdm
Sample pattern vector	28 (for training), 8 (for testing)
Learning rate, lr	0.8
Momentum constant, mc	0.8
Number of iteration	15000
Acceptable mean square error	0.0001
MSE at the end of training	3.01578e-005

Tab. III *Summary of ANN model.*

5. Conclusions

Speed, ability to learn from the experimental results and ease are the advantages of ANN when compared to classical method and it can also reduce the conduct of wide experimental study. Because of the above reasons ANN is chosen. This approach emerges to be a dominant tool in materials engineering and can be used efficiently as prediction technique in the area of material characterization and tribology. In this work, feed-forward backpropagation neural network is developed and used to calculate the mass loss of the newly developed alloys. For both training and testing of ANN, the experimental values of mass of the alloys are used. The error between the predicted value and experimental value is little, i.e., good compatibility with the experimental value and also this network can save much time. The overall performance of the model is relatively agreeable and it can be used to predict the mass loss with high accuracy.

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