Experimental Investigation and Prediction of Tribological Properties of Titanium Carbide and Multiwalled Carbon Nanotubes Reinforced Aluminium Composites using Artificial Neural Network

Mohamed Zakaulla, Anteneh M. Tahir, Seid Endro, Shemelis N. Wodaeneh and Lulseged Belay

***Abstract*—In this study, the tribological properties of TiC particle and MWCNTs reinforced aluminium (Al7475) hybrid composite synthesized by stir casting method were investigated by experimental and artificial neural network (ANN) model. Al7475 metal matrix composites was produced with different wt% of TiC and MWCNTs. The composite samples were tested at 0.42 ms^{-1}, 0.84 ms^{-1} and 1.68 ms^{-1} under three different loads (10N, 20N and 40N). The results indicated that Al7475+10%TiC+2%MWCNTs composite exhibit lower wear rate and reduced coefficient of friction in compare to other samples. TiC percent, MWCNTs percent, applied weight, sliding speed and Time were used as input values for the theoretical prediction model of the composite. Coefficient of friction and Wear loss were the two outputs developed from proposed network. Back propagation neural network with 5 – 6 – 2 architecture that uses Levenberg –Marquardt training algorithm is used to predict the coefficient of friction and wear loss. After comparing experimental and ANNs predicted results it was noted that R^2 was 0.992 for wear loss and 0.980 for coefficient of friction. This indicated that developed predicted model has a high state of reliability.**

***Index Terms*—Artificial Neural Network; Composites Friction; Wear.**

I. INTRODUCTION

Aluminium based composite material reinforced with ceramic and multiwalled carbon nanotubes (MWCNTs) have good tribological properties and hence they are of great interest for industries who manufacture tribomaterials [1]-[4]. For MWCNTs reinforced Al composites, simulation of tribological properties mostly imply the use of experimental data and predict excellently for complex conditions which endures in tribological test simulation. The prediction of tribological and mechanical properties of composite material using artificial neural network approach has been increasingly popular in last few years because it solves problem at a faster rate in compare to other approaches and it can also learn from small experimental data. Hakan Cetinel et al. [5] determined the wear loss of Mo coating which is deposited on ductile iron substrate. Plasma spray system is used for depositing Mo coatings on iron substrate and wear test were performed under different environment and load conditions. The numerical results obtained for wear and microhardness were compared with experimental results and agreement between two results is good. Adel et al. [6] predicted the porosity, hardness and density of Aluminium/copper based composite using feed forward back propogation neural network. It is observed that mean absolute relative error for porosity is 1.08%, 067% for density and 0.69% for hardness. Genel et al. [7] investigated the tribological behavior of Zinc aluminium composite reinforced with alumina fiber using Multilayered feed forward ANN network. Prediction of coefficient of friction and specific wear rate by ANN achieved the high degree of accuracy with 94.2% and 99.4%. Empirical expressions were established for friction coefficient and specific wear rate related to fiber volume fraction and load. Mostafa et al. [8] studied the electrical and hardness properties of Cu-Al2O3 composite using ANN approach. Designed ANN model predicted the results of hardness of Cu-Al2O3 composite with an average error of 5% and electrical conductivity of about 3%. Durson et al. [9] investigated the wear loss of A356 alloy reinforced with SiC synthesized by thixomoulding using experimental and artificial neural network approach. It was observed that developed prediction model has a high level of reliability as its R2 value is 0.9855.

In this paper, multilayer feed forward network which uses a Levenberg –Marquardt training algorithm with 5-6-2 architecture is developed A database comprising of various testing detais such as measuring condition, material composition and tribological characteristics of Al/TiC/MWCNTs composite was used to train and test the network. Subsequently, a well-trained neural network was used to predict coefficient of friction and wear loss in accordance to new input data. The attribute of prediction was also assessed. The result indicated neural network based wear prediction favored very feasible and encouraging for material design purposes and analyzing tribological properties for Al/TiC/MWCNTs composite are indicated in this study.

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M. Zakaulla is with the Kombolcha Institute of Technology, Department of Mechanical Engineering, Wollo University, Kombolcha, Ethiopia (mohd_zakaulla@yahoo.co.in).

A. M. Tahir is with the Kombolcha Institute of Technology, Department of Mechanical Engineering, Wollo University, Kombolcha, Ethiopia (anteneh67@gmail.com)

S. Endro is with the Kombolcha Institute of Technology, Department of Mechanical Engineering, Wollo University, Kombolcha, Ethiopia.

S. N. Wodaeneh is with Kombolcha Institute of Technology, Department of Mechanical Engineering, Wollo University, Kombolcha, Ethiopia.

L. Belayis with the Kombolcha Institute of Technology, Department of Mechanical Engineering, Wollo University, Kombolcha, Ethiopia (leulseged2020@gmail.com).

II. EXPERIMENTAL STUDY

In the manufacture of Al based metal matrix composites, the Al7475 is in billet form and TiC powder (<15µm) and also MWCNTs having length (<10 µm), outside dia (< 20 µm), Inner dia (<5 µm) were used. The manufacturing method involved is stir casting. In the manufacture of Al/TiC/MWCNTs composite, different wt% of TiC particles (2%, 4%, 6%, 8%, 10%) and MWCNTs (0.5%, 1%, 1.5%, 2%) were added in a Al7475 matrix as reinforcement phase. TiC particles and MWCNTs were mixed in a ball mill and later preheated to obtain a homogeneous dispersion of reinforcement phase. The preheated reinforcements were mixed in molten Al7475 at 750°C using automatic stirrer at a speed of 100 rpm. Wear test was performed under dry sliding condition using pin on disc sliding wear apparatus which has continous rotating steel plate of hardness 60RC. The wear test is performed as per ASTM G99 and load applied is 10, 20, 40N at a sliding speed of 0.42, 0.84 and 1.68m/s. wear loss in microns and frictional force is recorded using Windcom software.

III. ARTIFICIAL NEURAL NETWORK

ANN have highly interconnected structure in parity to brain cells of human neural network and comprises of neurons which are set out in different layers in network : an input layer, hidden layer and output layer. The pre-eminence of ANN is that it has efficacy to learn from sample set which is known as training set in a unsupervised or supervised learning process. Weights are calculated through learning process for the designed output when the architecture of network is defined. ANN has different topologies of architecture and they vary in terms of training strategy, architecture and learning process. All measured parameters are depicted in Table I.

TABLE I: MEASURED PARAMETERS FOR INPUT AND OUTPUT OF ANN

Input Material composition	Al7475 matrix	TiC particle (2, 4, 6, 8, 10 wt %)	MWCNTs (0, 0.5, 1, 1.5, 2 wt %)
Testing conditions	Sliding speed (0.42, 0.84, 1.68 m/s)	Load (10,20,40N)	Time (300, 600, 900, 1200,1500, 1800s).
Output	Coefficient of friction	Wear loss in microns(W_L)	

Network's performance for a developed ANN model is evaluated using Root mean square error (RMSE) and coefficient of determination (R^2). Low RMSE value and high R^2 value indicate that performance of model is good. For calculating RMSE and R2, Equation (1) and (2) were used.

$$RMSE = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(WLann - \Delta WLexp)^2\right)} \quad (1)$$

$$R^2 = 1 - \left(\frac{\sum((\Delta WLexp - \Delta WLann)^2)}{\sum((\Delta WLann)^2)}\right) \quad (2)$$

Individual ANN model must have inputs which are converted using normalization technique and should fall in closed interval [01]. The normalization technique is achieved using the equation (3).

$$Normalised\ value = \frac{Input\ value - minimum\ value}{maximum\ value - minimum\ value} \quad (3)$$

Output values obtained from ANN model should also be in the range [0 1] and converted to its tantamount values based on the method of normalization technique. Table II shows the normalization values.

TABLE II: NORMALIZATION VALUES

	Minimum value	Maximum value
TiC Weight percent	2	10
MWCNTs Weight percent	0	2
Applied load	10	40
Sliding speed	0.42	1.68
Time	300	1800
Wear loss in microns	9.13	179.69
Coefficient of friction	0.261	0.458

In the present study, a wear loss and coefficient of friction prediction model is developed using a Levenberg – Marquardt training algorithm. Activation function used for ANN model is sigmoid function which combines curvilinear, linear and constant behavior depending on the input values and is shown in equation (4).

$$y = f(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

The configuration is made of 5 inputs (TiC percent, MWCNTs percent, applied weight, sliding speed and Time), one hidden layer with 6 neurons and 2 output nodes (wear loss and coefficient of friction). Fig. 1 shows the Architecture of ANN and Table III depicts the parameters used for training the network.

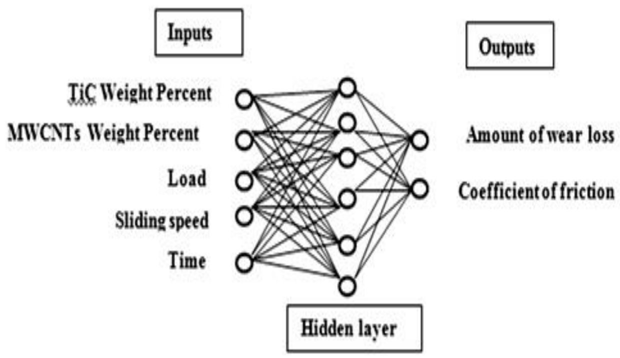

Fig. 1. Architecture of ANN

TABLE III: MULTILAYER PERCEPTRON ARCHITECTURE AND TRAINING PARAMETERS

Parameters	Value
The number of neurons on the layers	Input : 5, Hidden : 6, output: 2.
The initial weights and bases	Randomly between -1 and 1
Activation function for hidden and output layers	Sigmoid function
Training parameters learning rule	Back propogation
Training Algorithm	Levenberg –Marquardt
Number of iterations	1000
Initial mu	0.001
mu increase factor	10
mu decrease factor	0.1
Best validation performance	0.00071298

IV. Results and Discussions

A data set comprising of 250 experimental data points are employed to build a feed forward back propogation neural network. 240 data points are used for training the network and residuals are shown in Table IV which are used for testing the process and are not included in training the nework.

TABLE IV: Comparison of Results of Wear Loss Quantities and Coefficient of Friction in Wear Process of AL7475/TIC/MWCNTS Composite for Experimental Study and ANN Model

Experimental data					Experimental results		ANN results		% Error	
TiC wt%	MWCNTs wt%	Load (N)	Sliding speed (m/s)	Time (S)	Wear (μM)	Coefficient of friction	Wear (μM)	Coefficient of friction	Wear (μM)	Coefficient of friction
2	0	10	0.84	1800	60.78	0.412	61.28	0.419	0.81	1.60
4	0.5	10	0.42	1800	40.8	0.43	41.46	0.42	1.61	-1.65
4	0.5	20	0.84	1200	57.84	0.388	58.51	0.394	1.16	1.47
6	1	10	0.42	1800	36.79	0.403	37.19	0.41	1.08	1.5
6	1	20	1.68	600	45.58	0.337	46.32	0.341	1.60	1.13
8	1.5	10	0.42	900	19.78	0.401	20.30	0.395	2.57	-1.51
8	1.5	20	0.84	1200	42.59	0.353	43.23	0.358	1.50	1.25
8	1.5	40	0.42	1200	43.52	0.352	43.35	0.357	-0.38	1.23
10	2	10	0.84	1800	37.88	0.336	37.96	0.34	0.22	1.13

Wear loss data acquired by experimental study and ANN predicted values for testing and training process are shown in Fig. 2 and Fig. 3. The R^2 and RMSE value for wear loss training model and test prediction is shown in the Table V.

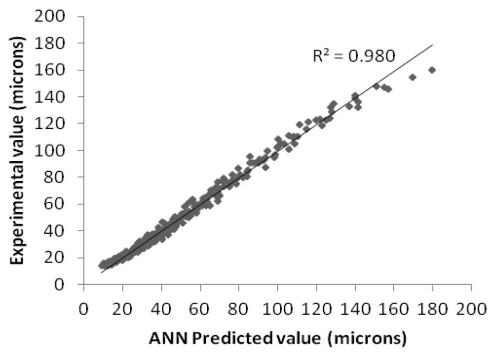

Fig. 2. Comparison of experimental and ANN training predicted results for wear loss.

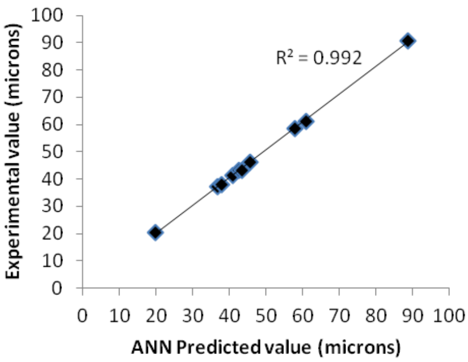

Fig. 3. Comparison of experimental and ANN test predicted results for wear loss

TABLE V: Statistical Values of ANN That Was Trained and Tested for Wear Loss.

Wear loss	R^2	RMSE
Training	0.980	2.45
Testing	0.992	0.55

As shown in the Fig. 4 and Fig. 5 the experimental results and ANN predicted results of training and testing for coefficient of friction are quite similar. The R^2 and RMSE value for coefficient of friction training model and test prediction is shown in the Table VI.

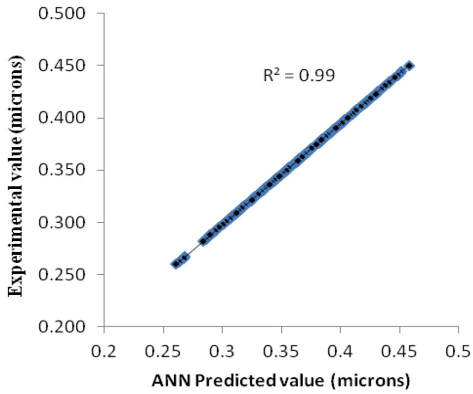

Fig. 4. Comparison of experimental and ANN training predicted results for Coefficient of friction

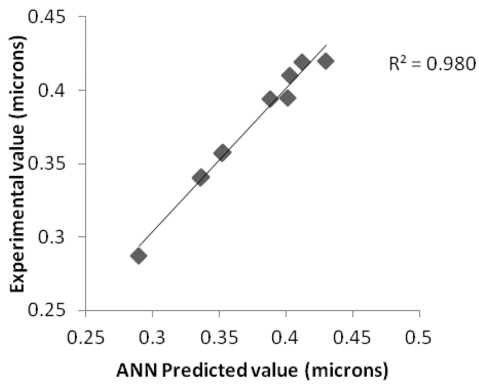

Fig. 5. Comparison of experimental and ANN test predicted results for Coefficient of friction.

TABLE VI: Statistical Values of ANN that was Trained and Tested for Coefficient of Friction.

Coefficient of friction	R^2	RMSE
Training	0.99	0.4
Testing	0.980	0.6

Fig. 6 and Fig. 7 shows the comparison between experimental and ANN values for wear loss and coefficient of friction for Al7475 composites as a function of time for 20N at 0.84 m/s. Experimental values are represented by continuous lines having ±5% error interval and ANN predicted results are represented by dashed lines. The error bar symbolizes the standard deviation of experimental values. It is obvious from the Fig. 6 and Fig. 7 that TiC and

MWCNTs have stronger effect on wear and friction resistance for Al7475 composites.

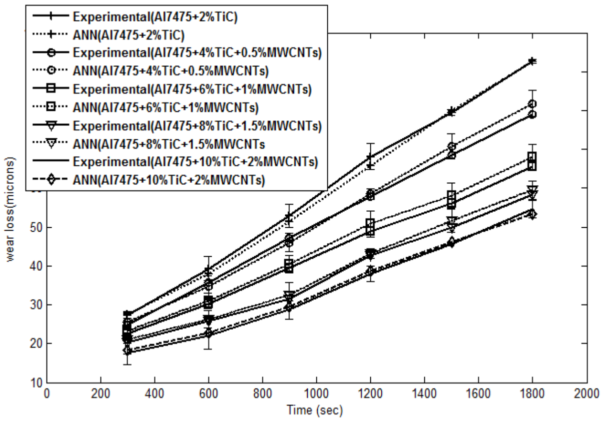

Fig. 6. Experimental vs. predicted values of wear loss as a function of time

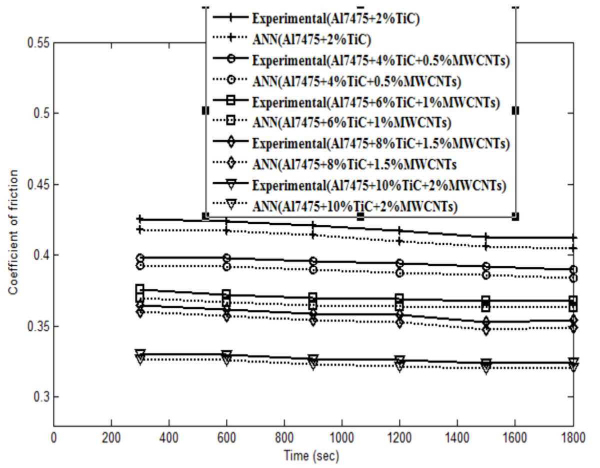

Fig. 7. Experimental vs. predicted values of Coefficient of friction as a function of time.

V. Conclusion

In this study, Al7475 alloy based metal matrix composites reinforced with different wt% of TiC and MWCNTs were produced using stir casting technique and tribological properties of this materials were examined. The experimental results and ANN predicted values using Feed forward back propagation neural network of Al7475+10%TiC+2%MWCNTs composite gives the best wear resistance and reduced coefficient of friction in compare to other Al7475 composites. The wear loss and coefficient of friction of Al7475 composites is predicted by the developed ANN model using various input parameters (TiC percent, MWCNTs percent, applied weight, sliding speed and Time). The predicted results of ANN models were compared with experimental results and the value of R^2 for ANN models is high for both wear loss (0.992) and coefficient of friction (0.980). Hence developed ANN models can be used for prediction of wear loss and coefficient of friction of Al7475/TiC/MWCNTs composites.

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