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A Machine Learning Advent in the Prediction Analysis of Wear Behavior of TiC Reinforced Al2219 Metal Matrix Composite

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Abstract-This paper aims at predicting the wear behavior of Al2219 alloy reinforced with TiC micro particles (in different weight fractions) in an unconventional way that leads to new latitude of soft computing. The dynamism of this work lies in the fact that it puts stress on mapping between two variegated domains of engineering i.e. Artificial Neural Network (ANN) is exercised on the province of Tribology. Wear is the problem of components that requires the replacement of the segments of assemblies frequently, thus making it necessary to minimize the wear rate. Feed Forward Back Propagation Network (FFBN) has been proven at its best in prediction using TANSIG and LOGSIG transfer functions due to the back propagation of the output errors, providing incomparable and significant accuracy. Hence this analysis of prediction emanating a new scope in the field of aerospace, aircraft, defense and automotive applications, is also an innovation in the discipline of Tribology.

Keywords-*Artificial Neural Network, Feed Forward Back Propagation, Hidden Layer, Regression, Transfer Function, Tribology*

1. Introduction

Tribology [21], the science of connecting surfaces in relative motion, deals with the study of wear, lubrication and friction. Wear [5] is the accelerating loss of matter from the surface of a solid body due to some mechanical action i.e. association or relative motion with a solid, gaseous or liquid obstructive body. Wear rate [2] is the volume loss per unit load per unit distance due to wear. Wear is a phenomenon due to which machines lose their durability and reliability and the parts of the machines have to be replaced more frequently. Hence the prediction of wear rate has become an essential need for the construction of reliable and durable machines and to ascertain the advancement of technology in future.

A Metal Matrix Composite (MMC) [4] is a composite material constituting at least two materials, one being a metal and the other can be a different metal or other material such as organic or ceramic. The matrix is the monolithic material into which reinforcement is added to enhance its physical properties such as friction coefficient, wear resistance and thermal conductivity. MMCs [20] are gradually entering the field of advanced aerospace application as an alluring material. These reinforced materials have been found of special importance due to their specific stiffness and specific strength. With the elevation of technology, there is an increasing demand of energy saving, cost-effective, stronger, light-weight and harder materials in the field of traffic engineering [3], aircraft, defense, space and automotive applications [10] and Aluminium Matrix Composites [9] are suitable in these spheres.

Aluminium and its alloys are widely used in industrial applications due to its wonderful combination of properties such as good corrosion resistance, easy to deform, better thermal conductivity and most importantly high strength to weight ratio for which it is used to manufacture automobile and aircraft components to make the moving vehicles lighter in weight and reduce the fuel consumption [16].

Aluminium alloy 2219 [10] is one kind of wrought alloy containing copper as a major element for blending. This copper makes this alloy suitable for heat treatment [17] that advances its tribological and mechanical properties. In this paper Al2219 was reinforced with Titanium Carbide (TiC) and the wear properties of this alloy were predicted before and after reinforcement with varying speed and load.

The prediction of wear rate in the laboratory suffers from various difficulties. Such a prediction is difficult to achieve because wear behavior depends on number of variables that change with time and scale. The factors are microstructure of the material, size and nature of wear debris, frictional heating, work hardening rate, environmental interactions and nature of abrasive particles. There are also other issues like manpower, cost engaging with the setup of laboratory instruments, less accuracy, time consumption and risk factors associated with adverse conditions. However ANN can predict the wear properties of MMCs very easily with high accuracy and much less manual effort and time.

Artificial Neural Network [7] is a computational model that is designed to simulate the way human brain processes and analyzes information and solves problems that are difficult to be solved by human or statistical standards. It is composed of huge number of highly interconnected processing elements called neurons. ANN has self-learning capability and it learns by detecting patterns and relationships in the provided data and arrives at the solution of a problem in a cost-effective way. It consists of three layers i.e. an input layer, one or more intermediate hidden layer and an output layer.

Nomenclature

T Tolerance

2. Background

This research mainly concentrates on the prediction analysis of wear behaviour of TiC reinforced Al2219 Metal Matrix Composite (MMC) using Artificial Neural Network. MMCs are being widely used in many industrial applications such as aircraft, defence, space, automobile industry etc because of their various properties that are well suited for these critical structural applications. Wear rate plays a major role in these applications as it depicts the rate of decay of a material with applied load or speed. Thus it should be as much less as possible for a good structural application and research must be carried out to minimize it. Many investigations have been done on the effect of reinforcement added to these Metal Matrices to enhance the wear properties of these materials. An investigation of the wear properties of Al2219 alloy before and after introducing TiC micro particles was made [10]. This work has made the basis of this research. There was an attempt to develop and study the wear properties of Al7025-B_4C reinforced aluminium MMC [3]. An experiment was performed to produce particulate Al-graphite composites with superior wear resistance [16]. Sliding wear tests were conducted of As cast Al alloy, Al alloy reinforced with SiC particles and Al alloy reinforced with SiCp-Graphite at various load, speed and sliding distances [4]. An investigation was done on the wear behaviour of Al alloy LM25 reinforced with SiC particulate and further addition of TiO_2 particulate [9]. All these works have been done using a conventional approach to study the wear behaviour of MMCs. ANN can predict the wear behaviour of MMCs much more easily than a conventional approach and many researchers have proved that. ANN approach was used for the prediction of effect of reinforcement and deformation on volumetric wear of red mud nano particle reinforced Al matrix composites synthesized by stir casting method [19].

A neural network model was developed to predict the abrasive wear behaviour of Al2024-B_4C composite [6]. ANN was used to predict the wear properties of Al6061-TiO_2 composite [11]. ANN has also been used to predict the wear rate of Al matrix composites after different reinforcement addition [8]. [15], [12], [1], [14], and [18] are also some contributions made by researchers in this field. The most promising research made was [13] that motivated this research with the guidelines of prediction capabilities of neural networks. However, in these works the comparison of transfer functions are not prominent enough. Hence in this particular work it is enhanced that the nature of prediction along with transfer functions is dependent on the alloy on which ANN is applied.

3. Diagrammatic epitome

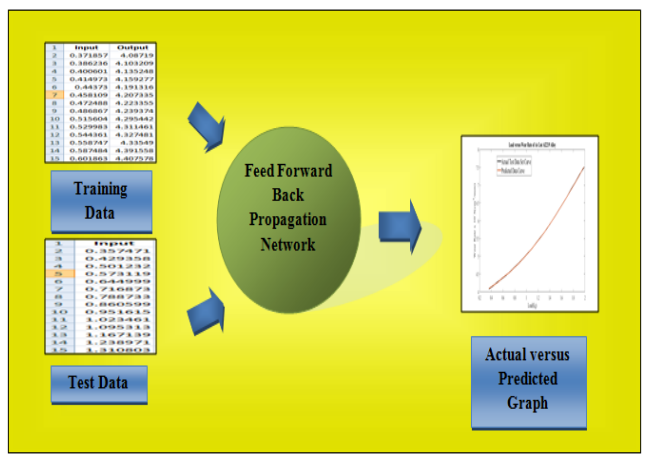

Fig. 1 Illustrative recapitulation of the entire work

This diagram illustrates the whole work in a pictorial mode. The training and test data were provided to the FFBN and it gave as output the predicted graph plotted on the actual one.

4. Implementation technique

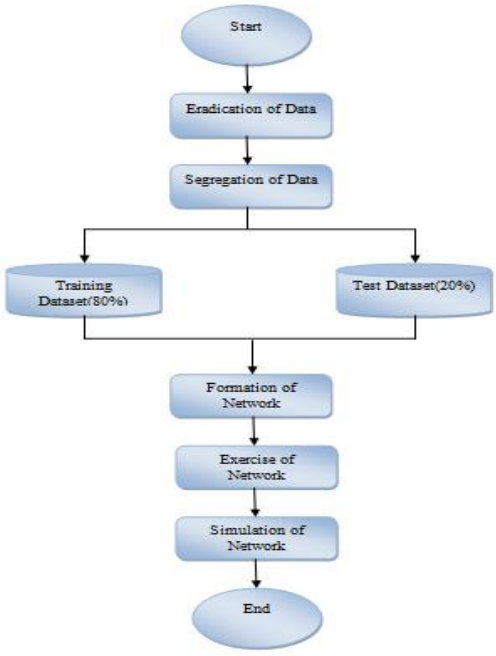

Fig. 2 Flow chart of archetype of the implementation technique

4.1 Eradication of data

The very first thing to be done to predict the tribological behavior of TiC reinforced Al2219 alloy is the extraction of dataset from the original graph. The accuracy of prediction highly depends on the nature of the dataset for training the network. Hence, data eradication was done for the prediction of wear rate with varying speed, load and weight fraction of TiC particles.

4.2 Segregation of data

The extracted dataset was subdivided in two datasets. Those are:

- Training Dataset
- Test Dataset

Training and test dataset contain 80% and 20% of the whole dataset and was used for training the network and simulating the test performance i.e. prediction of the wear rate respectively. Training dataset was further divided into input and output datasets.

4.3 Formation of network

The next step after the segregation of data is to build up the network. First the input, output and test datasets were imported. Then the network name was given and various network parameters i.e. network type, input data, target data, training function, adaptation learning function, performance function, number of layers, number of neurons in the hidden layer and transfer function (TANSIG, LOGSIG or PURELIN) were selected.

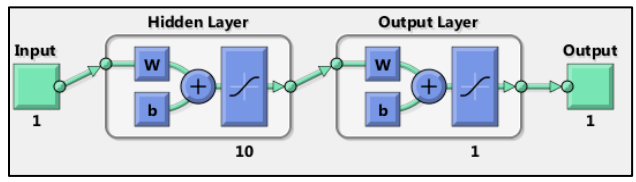

Fig. 3 Layout of the ANN after formation of the network

4.4 Exercise of network

After building up the network the same was trained for a number of times to improve the performance. In this step several training parameters were set up. The training parameters in this work were the epoch, learning rate and momentum which were kept constant throughout the process.

Table 1: The training parameters

Epoch	*Learning rate*	*Momentum*
1000	0.001	0.01

4.5 Simulation of network

The regression was analysed and if it seemed to be good training, then the network was simulated using the test dataset. Then the output and error files were exported and the actual and predicted graphs were plotted upon one another. If the result was as expected, then the prediction was successful and the Mean Squared Error (MSE) and accuracy percentage were calculated. Otherwise another network was built up using different number of neurons in the hidden layer and the whole process was carried out to improve the prediction.

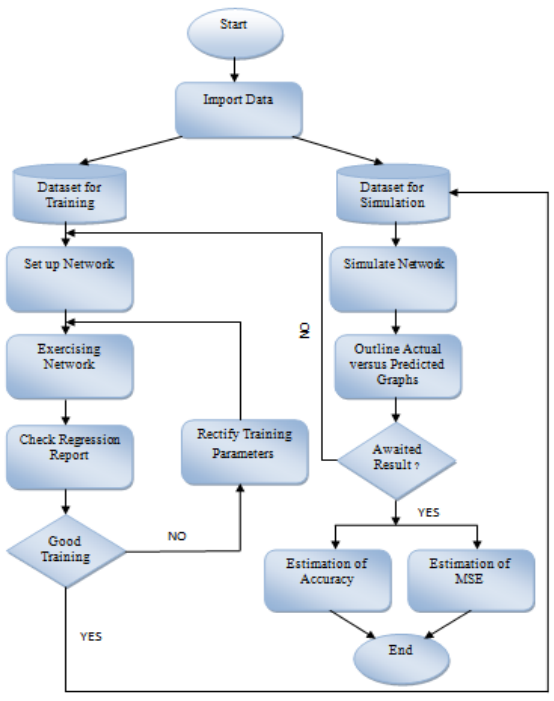

Fig. 4 Flow chart of the entire proceeding of Feed Forward Back Propagation Network in ANN

MATLAB is a multi paradigm programming language and numerical computing platform developed by MathWorks and it was designed specifically for engineers and scientists. It integrates visualization, computation and programming in an easy-to-use environment where problem and solutions are expressed in familiar mathematical notations. MATLAB provides a huge range of applications including machine learning and deep learning, image and video processing, signal processing and communications, computational finance, control systems, test and measurement and computational biology.

In this paper, MATLAB R2017a was used for the implementation of machine learning in the realm of Tribology. The above illustrated flow chart depicts the entire operation carried out on MATLAB in order to predict the wear behavior of TiC reinforced Al2219 alloy.

5. Data specification

This paper focuses on predicting the wear rate of Al2219 alloy before and after the reinforcement with TiC particles. This experiment was carried out with varying speed, load and weight fraction of the reinforcement. The wear rate was predicted of unreinforced Al2219 alloy and 2%, 4% and 6% TiC particulate reinforced MMC.

5.1 Original graph

The dataset contains two graphs [10] depicting the relation between wear rate & load and wear rate & speed. The first graph shows the variation of wear rate as a function of load at 800 rpm constant sliding speed of Al2219 alloy at various concentrations (0% to 6%) of TiC particles. It is evident from the graph that the wear rate of unreinforced and reinforced Al2219 alloy increases with the increasing load from 0.5 to 2 kg. It can also be observed that the wear rate of Al2219 alloy decreases with the increase in the weight fraction of TiC particles.

The second graph shows the variation of wear rate at varying speed and 2 kg constant load of TiC reinforced Al2219 alloy (in weight fraction 0% to 6%). Here also the wear rate of Al2219 alloy and its composites is increasing with the increment of speed from 600 to 900 rpm. It is also clear from the graph that the wear rate decreases with the increasing weight fraction of TiC particles in Al2219 alloy.

5.2 Predicted graph

The wear rate of TiC reinforced Al2219 alloy was predicted using the Feed Forward Back Propagation Network of ANN using TANSIG, LOGSIG and PURELIN transfer functions with varying hidden layers to improve the prediction accuracy. The predicted graphs were plotted on the actual graphs to show the accuracy of prediction. However the predicted graphs are not the entire original graphs rather 20% data extracted from the original data set. The black curve shows the actual test data set curve and the red one shows the predicted curve.

6. Outcome analysis

6.1 Result analysis for load versus wear rate of unreinforced As cast Al2219 alloy

Table 2: The performance of different number of neurons in the hidden layer for TANSIG transfer function

No. of neurons in Hidden Layer=10		***No. of neurons in Hidden Layer=20***		***No. of neurons in Hidden Layer=25***	
T	***Accuracy (%)***	***T***	***Accuracy (%)***	***T***	***Accuracy (%)***
0.01	100	0.01	100	0.01	100
-	100	-	95.65	-	86.97

Table 3: The performance of LOGSIG transfer function

No. of Neurons in Hidden Layer = 10	
T	***Accuracy (%)***
0.01	100
-	100

Table 4: MSE and regression values of the transfer functions

Transfer Function	***MSE***	***R Value***		
		Training	***Test***	***All***
TANSIG	4.4481E-05	0.99998	0.99997	0.99998
LOGSIG	4.6953E-05	0.99998	0.99997	0.99998
PURELIN	1.0600E-02	0.99488	0.99794	0.99516

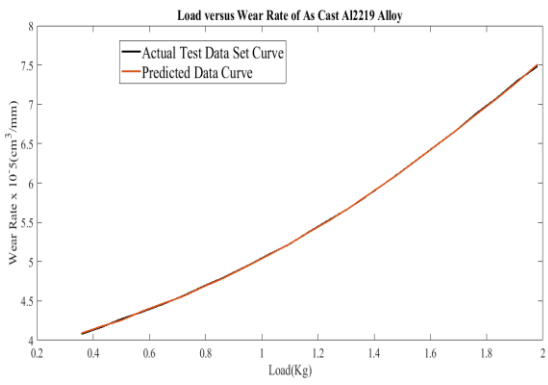

Fig. 5 Outline of actual versus predicted graph using TANSIG transfer function for 10 neurons in the hidden layer

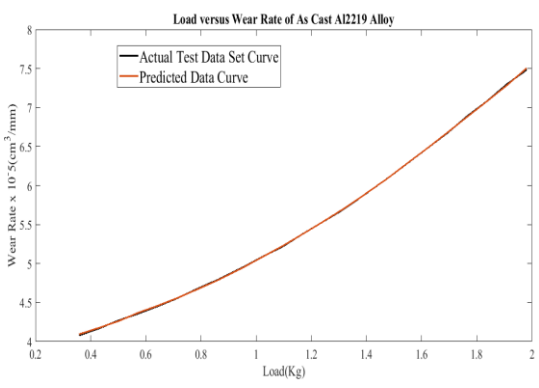

Fig. 6 Outline of actual versus predicted graph using LOGSIG transfer function for 10 neurons in the hidden layer

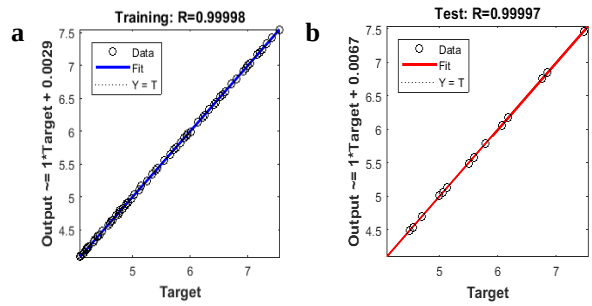

Fig. 7 (a) Training regression of TANSIG transfer function for 10 neurons in the hidden layer (b) Test regression of TANSIG transfer function for 10 neurons in the hidden layer

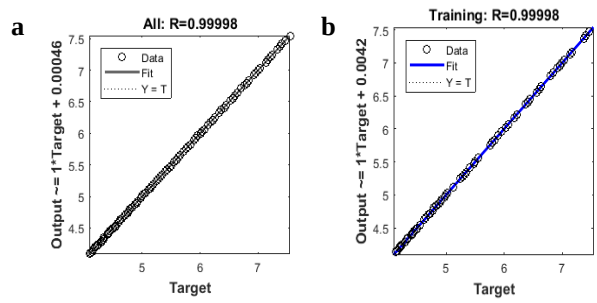

Fig. 8 (a) All regression of TANSIG transfer function for 10 neurons in the hidden layer (b) Training regression of LOGSIG transfer function for 10 neurons in the hidden layer

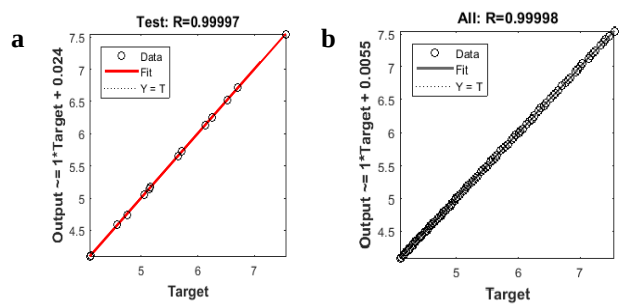

Fig. 9 (a) Test regression of LOGSIG transfer function for 10 neurons in the hidden layer (b) All regression of LOGSIG transfer function for 10 neurons inthe hidden layer

The analysis of the dataset for Load versus Wear Rate of As-cast Al2219 alloy was done on different number of neurons in the hidden layer using TANSIG transfer function. The observation was that the accuracy percentages were same (i.e. 100%) for tolerance values 0.01, 0.02 and 0.03 for 10, 20 and 25 neurons in the hidden layer. Moreover, the dataset achieved 100% accuracy without considering any tolerance for 10 numbers of neurons in the hidden layer (Table: 2). So, it was concluded that the analysis for Load versus Wear Rate of As-cast Al2219 alloy must be carried out using 10 neurons in the hidden layer.

After that for a comparative study, the same analysis was done using LOGSIG transfer function for 10 neurons in the hidden layer. It was observed that the accuracy percentages were 100% (Table: 3) for all the above mentioned tolerance values for LOGSIG transfer function. Then for resolving the conflict that which transfer function performs the best, the MSE values of these transfer functions were calculated (Table: 4), after training was done. The MSE values of TANSIG and LOGSIG were 4.4481E-05 (i.e. 0.000044) and 4.6953E-05 (i.e. 0.000046). The MSE value of LOGSIG transfer function being slightly greater than that of TANSIG transfer function, it was concluded that the analysis should be carried out using TANSIG transfer function.

Besides, the analysis was also done using PURELIN function with the same number of neurons and the MSE value was 1.0600E-02 (i.e. 0.0106), which was much greater than that of the other two functions. Hence, it was proved that PURELIN performs the worst.

From the above discussion it was concluded that the analysis for Load versus Wear Rate of As-cast Al2219 alloy should be done using **TANSIG transfer function for 10 numbers of neurons in the hidden layer.**

6.2 Result analysis for load versus wear rate of 2% TiC reinforced Al2219 alloy

Table 5: The performance of different number of neurons in the hidden layer for TANSIG transfer function

No. of neurons in Hidden Layer=15		*No. of neurons in Hidden Layer=20*		*No. of neurons in Hidden Layer=25*	
T	***Accuracy (%)***	***T***	***Accuracy (%)***	***T***	***Accuracy (%)***
0.01	100	0.01	100	0.01	100
-	96.15	-	100	-	92.31

Table 6: The performance of LOGSIG transfer function

No. of Neurons in Hidden Layer = 20	
T	***Accuracy (%)***
0.01	100
-	76.92

Table 7: MSE and regression values of the transfer functions

Transfer Function	***MSE***	***R Value***		
		Training	***Test***	***All***
TANSIG	5.4094E-05	0.99997	0.99995	0.99996
LOGSIG	2.0113E-04	0.99984	0.99993	0.99986
PURELIN	1.3533E-03	0.99905	0.9996	0.99921

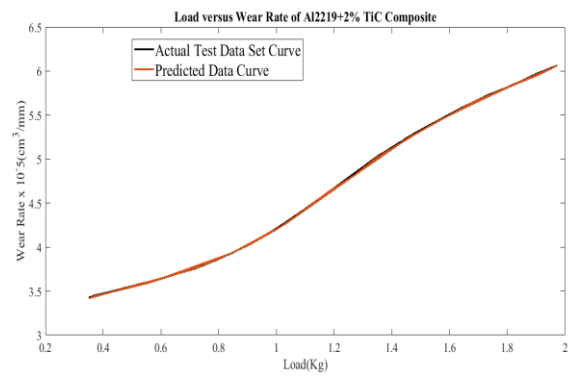

Fig. 10 Outline of actual versus predicted graph using TANSIG transfer function for 20 neurons in the hidden layer

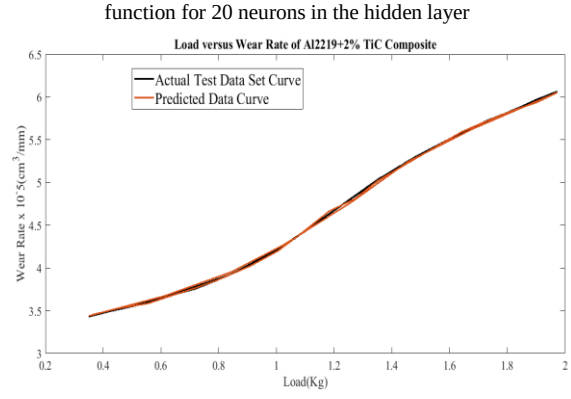

Fig. 11 Outline of actual versus predicted graph using LOGSIG transfer function for 20 neurons in the hidden layer

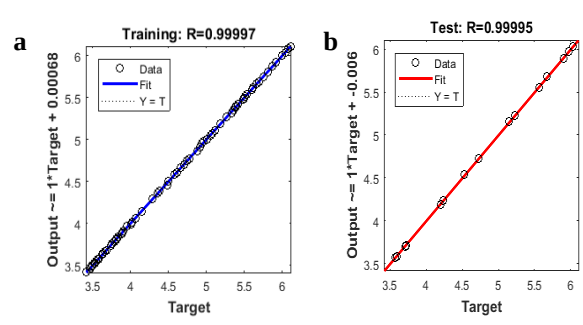

Fig. 12 (a) Training regressionof TANSIG transfer function for 20 neurons in the hidden layer (b) Test regression of TANSIG transfer function for 20 neurons in the hidden layer

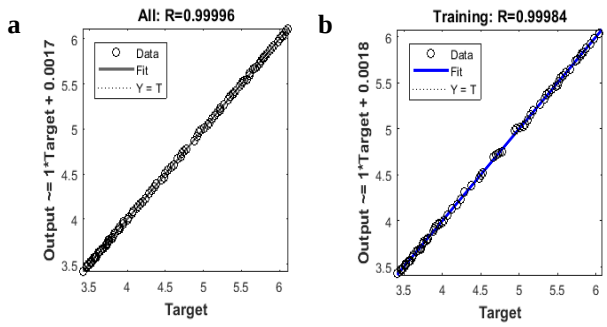

Fig. 13 (a) All regression of TANSIG transfer function for 20 neurons in the hidden layer (b) Training regression of LOGSIG transfer function for 20 neurons in the hidden layer

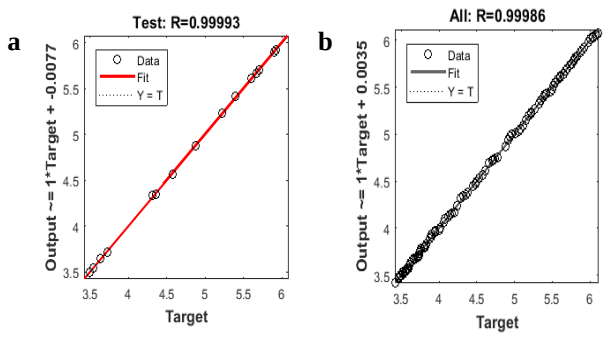

Fig. 14 (a) Test regression of LOGSIG transfer function for 20 neurons in the hidden layer (b) All regression of LOGSIG transfer function for 20 neurons inthe hidden layer

6.3 Result analysis for load versus wear rate of 4% TiC reinforced Al2219 alloy

Table 8: The performance of different number of neurons in the hidden layer for TANSIG transfer function

No. of neurons in Hidden Layer=10		*No. of neurons in Hidden Layer=15*		*No. of neurons in Hidden Layer=20*	
T	***Accuracy (%)***	***T***	***Accuracy (%)***	***T***	***Accuracy (%)***
0.01	100	0.01	100	0.01	100
-	100	-	85.71	-	80.95

Table 9: The performance of LOGSIG transfer function

No. of Neurons in Hidden Layer = 10	
T	***Accuracy (%)***
0.01	100
-	95.24

Table 10: MSE and regression values of the transfer functions

Transfer Function	***MSE***	***R Value***		
		Training	***Test***	***All***
TANSIG	5.3593E-05	0.99996	0.99994	0.99995
LOGSIG	5.0509E-05	0.99996	0.99994	0.99996
PURELIN	8.1705E-05	0.99936	0.99912	0.99933

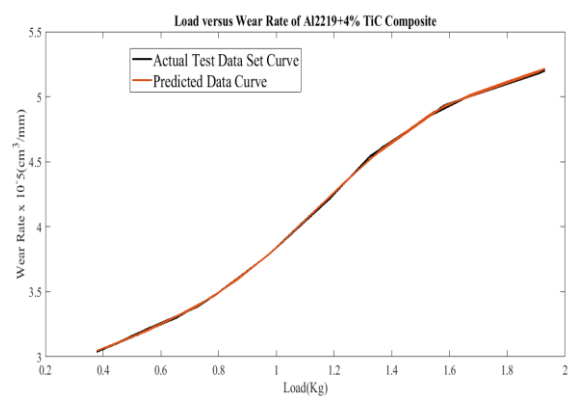

Fig. 15 Outline of actual versus predicted graph using TANSIG transfer function for 10 neurons in the hidden layer

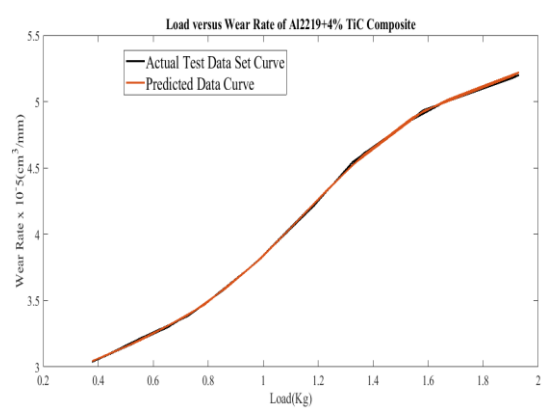

Fig. 16 Outline of actual versus predicted graph using LOGSIG transfer function for 10 neurons in the hidden layer

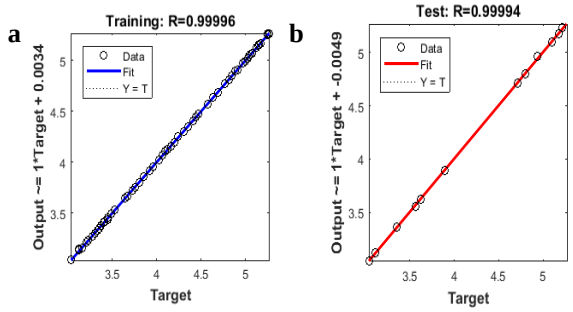

Fig. 17 (a) Training regression of TANSIG transfer function for 10 neurons in the hidden layer (b) Test regression of TANSIG transfer function for 10 neurons in the hidden layer

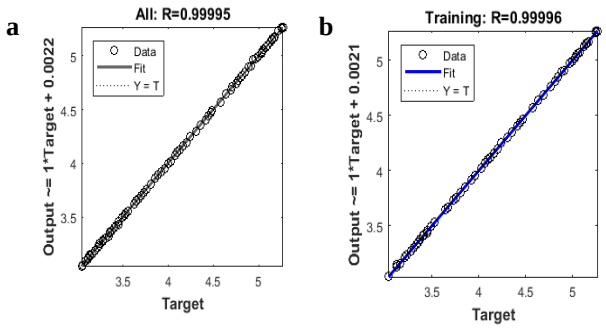

Fig. 18 (a) All regression of TANSIG transfer function for 10 neurons in the hidden layer (b) Training regression of LOGSIG transfer function for 10 neurons in the hidden layer

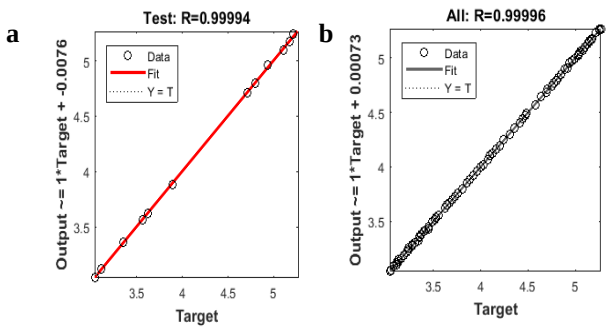

Fig. 19 (a) Test regression of LOGSIG transfer function for 10 neurons in the hidden layer (b) All regression of LOGSIG transfer function for 10 neurons in the hidden layer

6.4 Result analysis for load versus wear rate of 6% TiC reinforced Al2219 alloy

Table 11: The performance of different number of neurons in the hidden layer for TANSIG transfer function

No. of neurons in Hidden Layer=5		*No. of neurons in Hidden Layer=10*		*No. of neurons in Hidden Layer=15*	
T	***Accuracy (%)***	***T***	***Accuracy (%)***	***T***	***Accuracy (%)***
0.01	100	0.01	100	0.01	100
-	90.48	-	80.95	-	95.24

Table 12: The performance of LOGSIG transfer function

No. of Neurons in Hidden Layer = 15	
T	***Accuracy (%)***
0.01	100
-	80.95

Table 13: MSE and regression values of the transfer functions

Transfer Function	***MSE***	***R Value***		
		Training	***Test***	***All***
TANSIG	4.1977E-05	0.99996	0.99992	0.99994
LOGSIG	7.1336E-05	0.99990	0.99990	0.99990
PURELIN	5.9385E-04	0.99932	0.99924	0.99924

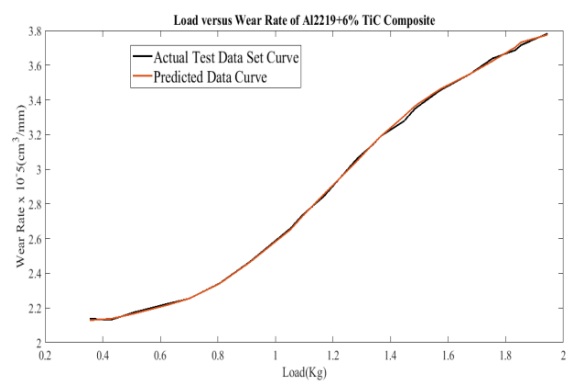

Fig. 20 Outline of actual versus predicted graph using TANSIG transfer function for 15 neurons in the hidden layer

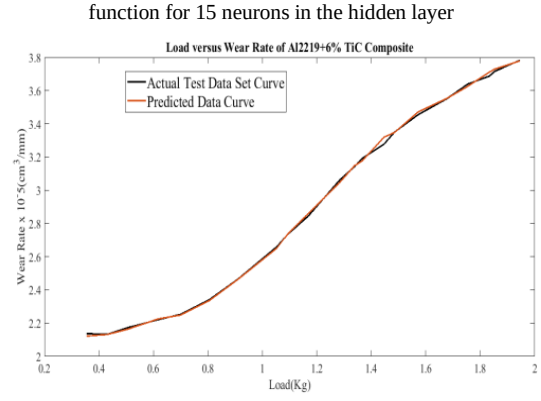

Fig. 21 Outline of actual versus predicted graph using LOGSIG transfer function for 15 neurons in the hidden layer

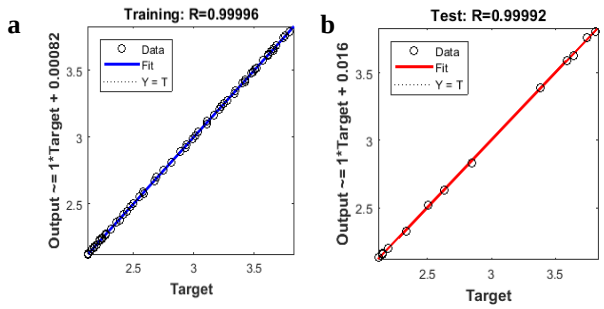

Fig. 22 (a) Training regression of TANSIG transfer function for 15 neurons in the hidden layer (b) Test regression of TANSIG transfer function for 15 neurons in the hidden layer

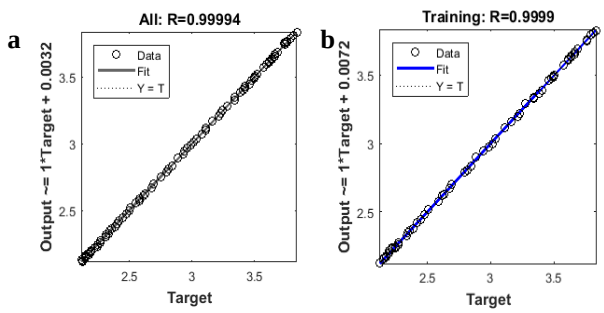

Fig. 23 (a) All regression of TANSIG transfer function for 15 neurons in the hidden layer (b) Training regression of LOGSIG transfer function for 15 neurons in the hidden layer

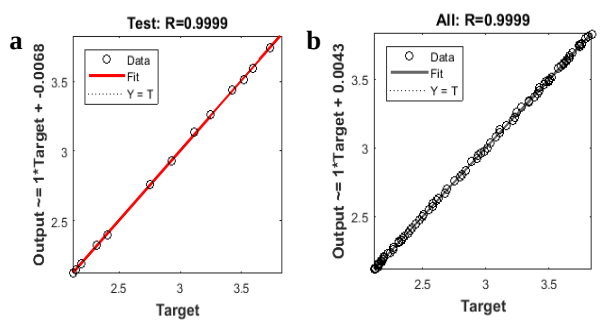

Fig. 24 (a) Test regression of LOGSIG transfer function for 15 neurons in the hidden layer (b) All regression of LOGSIG transfer function for 15 neurons inthe hidden layer

6.5 Result analysis for speed versus wear rate of unreinforced As cast Al2219 alloy

Table 14: The performance of different number of neurons in the hidden layer for TANSIG transfer function

No. of neurons in Hidden Layer=10		*No. of neurons in Hidden Layer=25*		*No. of neurons in Hidden Layer=45*	
T	***Accuracy (%)***	***T***	***Accuracy (%)***	***T***	***Accuracy (%)***
0.01	100	0.01	100	0.01	100
-	100	-	96.15	-	92.31

Table 15: The performance of LOGSIG transfer function

No. of Neurons in Hidden Layer = 10	
T	***Accuracy (%)***
0.01	100
-	100

Table 16: MSE and regression values of the transfer functions

Transfer Function	***MSE***	***R Value***		
		Training	***Test***	***All***
TANSIG	2.4506E-05	0.99997	0.99997	0.99997
LOGSIG	3.8445E-05	0.99996	0.99993	0.99995
PURELIN	7.8960E-04	0.99932	0.99910	0.99924

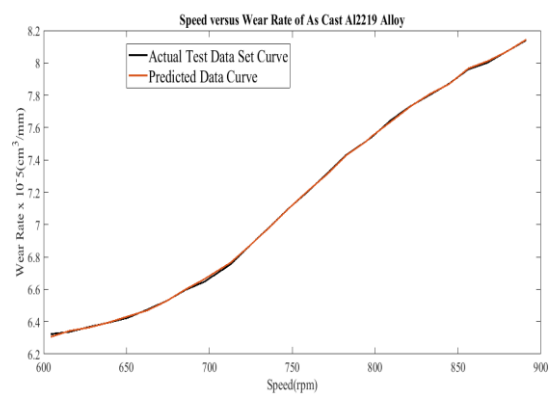

Fig. 25 Outline of actual versus predicted graph using TANSIG transfer function for 10 neurons in the hidden layer

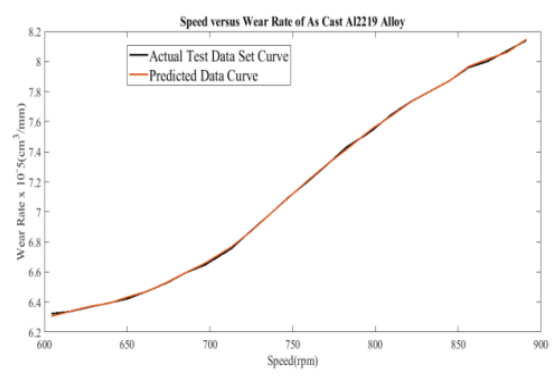

Fig. 26 Outline of actual versus predicted graph using LOGSIG transfer function for 10 neurons in the hidden layer

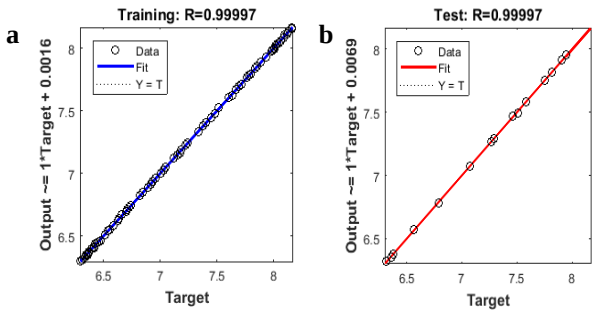

Fig. 27 (a) Training regression of TANSIG transfer function for 10 neurons in the hidden layer (b) Test regression of TANSIG transfer function for 10 neurons in the hidden layer

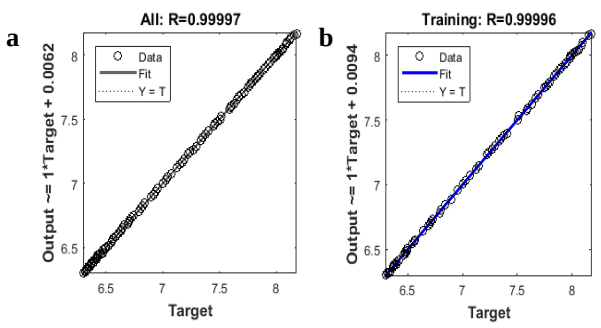

Fig. 28 (a) All regression of TANSIG transfer function for 10 neurons in the hidden layer (b) Training regression of LOGSIG transfer function for 10 neurons in the hidden layer

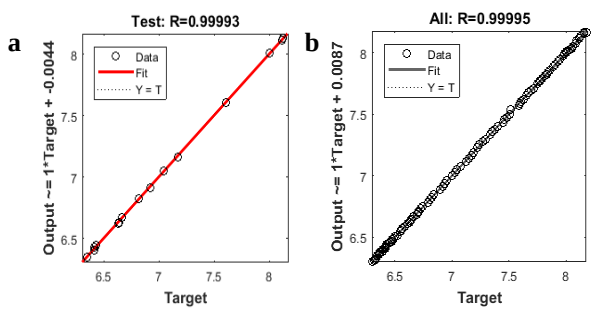

Fig. 29 (a) Test regression of LOGSIG transfer function for 10 neurons in the hidden layer (b) All regression of LOGSIG transfer function for 10 neurons inthe hidden layer

6.6 Result analysis for speed versus wear rate of 2% TiC reinforced Al2219 alloy

Table 17: The performance of different number of neurons in the hidden layer for TANSIG transfer function

No. of neurons in Hidden Layer=10		***No. of neurons in Hidden Layer=20***		***No. of neurons in Hidden Layer=40***	
T	***Accuracy (%)***	***T***	***Accuracy (%)***	***T***	***Accuracy (%)***
0.01	100	0.01	100	0.01	100
-	96.30	-	100	-	92.59

Table 18: The performance of LOGSIG transfer function

No. of Neurons in Hidden Layer = 20	
T	***Accuracy (%)***
0.01	100
-	100

Table 19: MSE and regression values of the transfer functions

Transfer Function	***MSE***	***R Value***		
		Training	***Test***	***All***
TANSIG	3.5164E-05	0.99995	0.99997	0.99995
LOGSIG	5.1127E-05	0.99991	0.99994	0.99992
PURELIN	7.8932E-03	0.98737	0.99303	0.98824

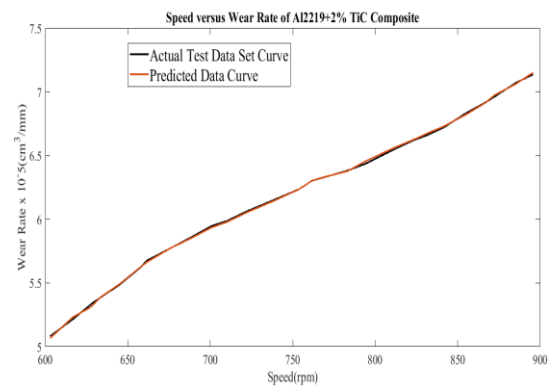

Fig. 30 Outline of actual versus predicted graph using TANSIG transfer function for 20 neurons in the hidden layer

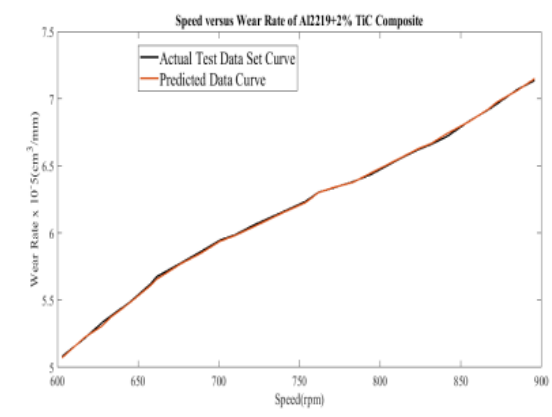

Fig. 31 Outline of actual versus predicted graph using LOGSIG transfer function for 20 neurons in the hidden layer

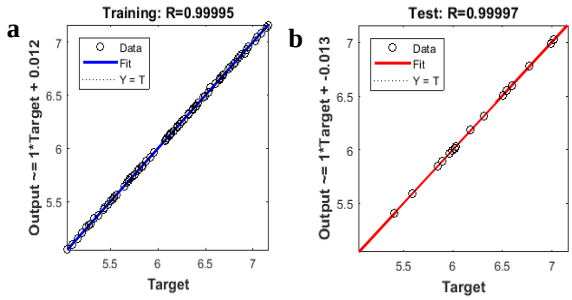

Fig. 32 (a) Training regression of TANSIG transfer function for 20 neurons in the hidden layer (b) Test regression of TANSIG transfer function for 20 neurons in the hidden layer

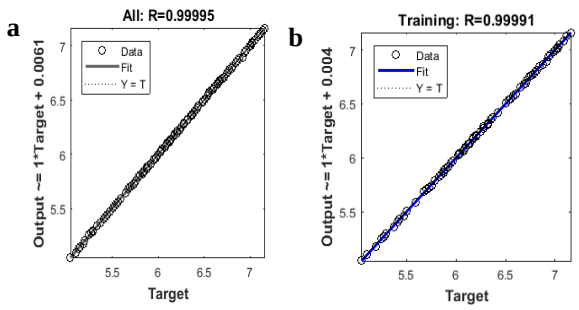

Fig. 33 (a) All regression of TANSIG transfer function for 20 neurons in the hidden layer (b) Training regression of LOGSIG transfer function for 20 neurons in the hidden layer

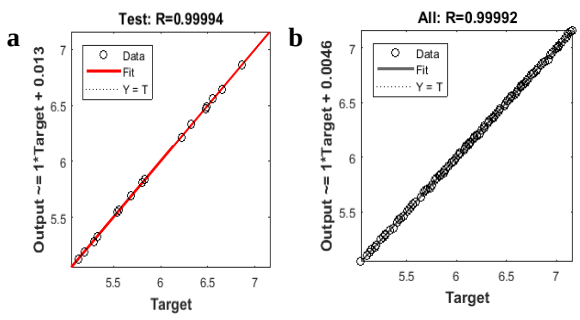

Fig. 34 (a) Test regression of LOGSIG transfer function for 20 neurons in the hidden layer (b) All regression of LOGSIG transfer function for 20 neurons in the hidden layer

6.7 Result analysis of speed versus wear rate of 4% TiC reinforced Al2219 alloy

Table 20: The performance of different number of neurons in the hidden layer for TANSIG transfer function

No. of neurons in Hidden Layer=10		*No. of neurons in Hidden Layer=30*		*No. of neurons in Hidden Layer=50*	
T	*Accuracy (%)*	*T*	*Accuracy (%)*	*T*	*Accuracy (%)*
0.01	100	0.01	100	0.01	92.59
-	100	-	85.19	-	77.78

Table 21: The performance of LOGSIG transfer function

No. of Neurons in Hidden Layer = 10	
T	*Accuracy (%)*
0.01	100
-	100

Table 22: MSE and regression values of the transfer functions

Transfer Function	*MSE*	*R Value*		
		Training	*Test*	*All*
TANSIG	4.1192E-05	0.99991	0.99993	0.99991
LOGSIG	4.6397E-05	0.99991	0.99982	0.99990
PURELIN	7.2389E-03	0.98575	0.98741	0.98500

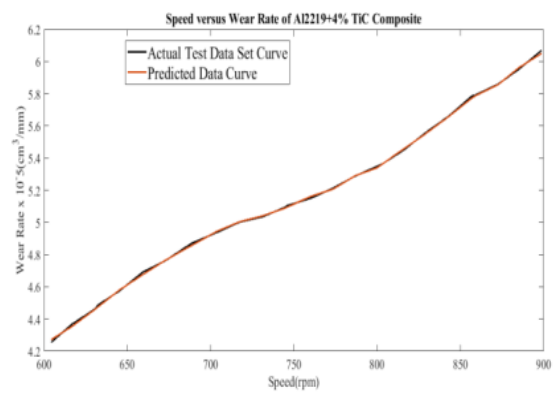

Fig. 35 Outline of actual versus predicted graph using TANSIG transfer function for 10 neurons in the hidden layer

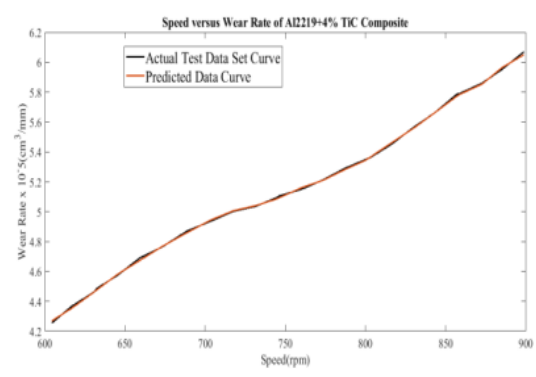

Fig. 36 Outline of actual versus predicted graph using LOGSIG transfer function for 10 neurons in the hidden layer

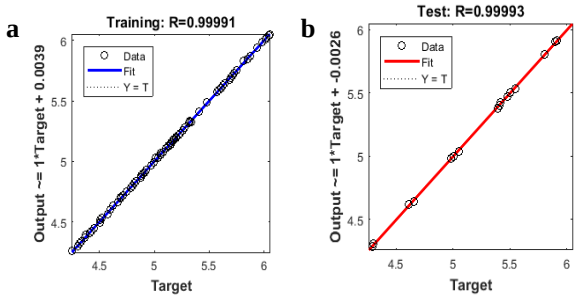

Fig. 37 (a) Training regression of TANSIG transfer function for 10 neurons in the hidden layer (b) Test regression of TANSIG transfer function for 10 neurons in the hidden layer

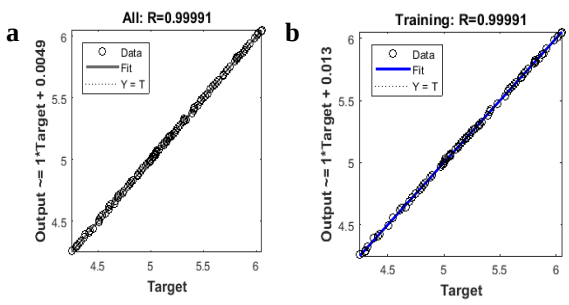

Fig. 38 (a) All regression of TANSIG transfer function for 10 neurons in the hidden layer (b) Training regression of LOGSIG transfer function for 10 neurons in the hidden layer

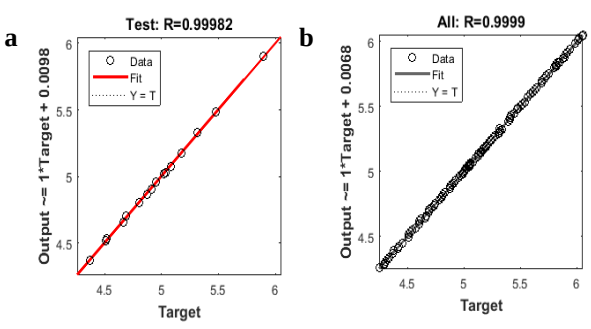

Fig. 39 (a) Test regressionof LOGSIG transfer function for 10 neurons in the hidden layer (b) All regression of LOGSIG transfer function for 10 neurons inthe hidden layer

6.8 Result analysis for speed versus wear rate of 6% TiC reinforced Al2219 alloy

Table 23: The performance of different number of neurons in the hidden layer for TANSIG transfer function

No. of neurons in Hidden Layer=5		*No. of neurons in Hidden Layer=10*		*No. of neurons in Hidden Layer=30*	
T	*Accuracy (%)*	*T*	*Accuracy (%)*	*T*	*Accuracy (%)*
0.01	100	0.01	100	0.01	100
-	92	-	88	-	84

Table 24: The performance of LOGSIG transfer function

No. of Neurons in Hidden Layer = 5	
T	*Accuracy (%)*
0.01	100
-	96

Table 25: MSE and regression values of the transfer functions

Transfer Function	*MSE*	*R Value*		
		Training	*Test*	*All*
TANSIG	7.4450E-05	0.99981	0.99986	0.99980
LOGSIG	7.5337E-05	0.99978	0.99988	0.99980
PURELIN	16676E-03	0.99590	0.99613	0.99577

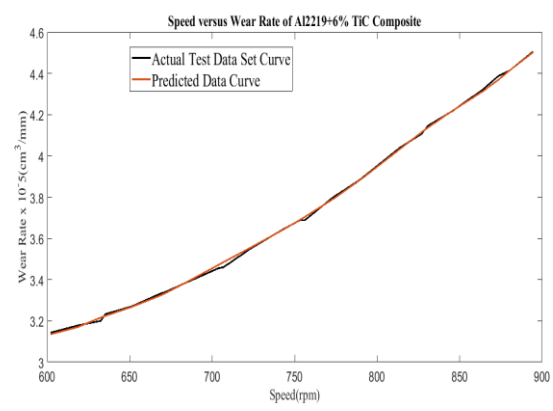

Fig. 40 Outline of actual versus predicted graph using TANSIG transfer function for 5 neurons in the hidden layer

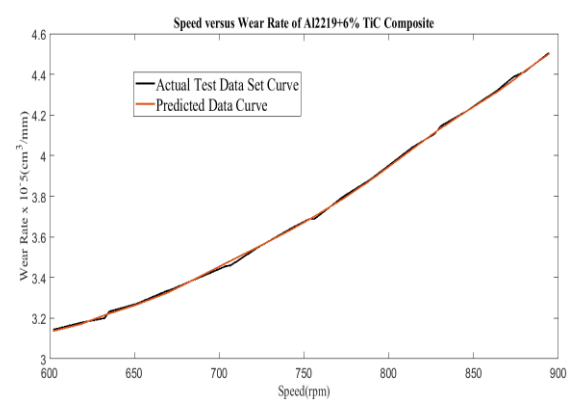

Fig. 41 Outline of actual versus predicted graph using LOGSIG transfer function for 5 neurons in the hidden layer

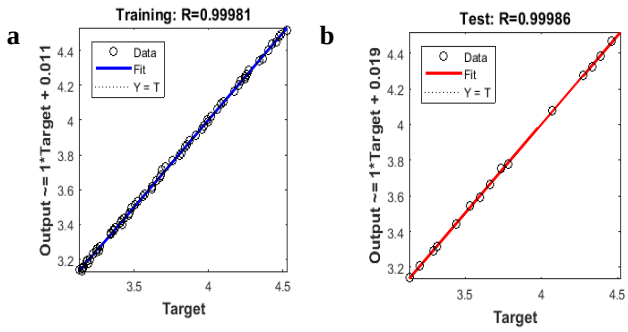

Fig. 42 (a) Training regression of TANSIG transfer function for 5 neurons in the hidden layer (b) Test regression of TANSIG transfer function for 5 neurons in the hidden layer

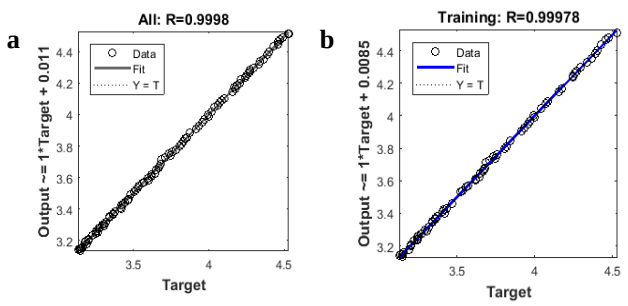

Fig. 43 (a) All regression of TANSIG transfer function for 5 neurons in the hidden layer (b) Training regression of LOGSIG transfer function for 5 neurons in the hidden layer

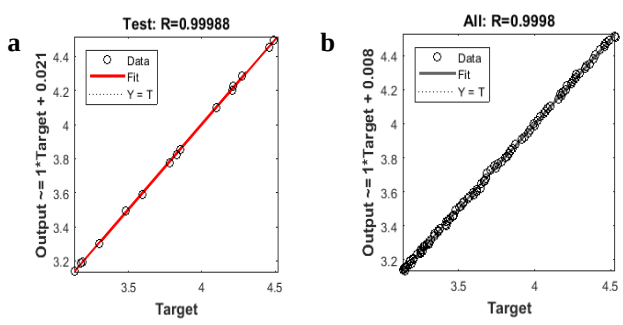

Fig. 44 (a) Test regressionof LOGSIG transfer function for 5 neurons in the hidden layer (b) All regression of LOGSIG transfer function for 5 neurons inthe hidden layer

7. Conclusion

The investigation and outcome interprets the triumph of application of Machine Learning and Soft Computing in the terrain of Tribology in predicting the wear behaviour of TiC reinforced Al2219 alloy. This research focuses mainly on the behavioural changes of FFBN along with its different transfer functions. The most promising analytical result was achieved when it was found that there is no such specific transfer function that can behave well on a specific dataset. It was achieved that different transfer functions performs the best on different datasets (Table: 26, 27). Finally it can be concluded that the sole behaviour of the ANN is highly constrained by the particular dataset on which it is applied for prediction. It opens up the region of applicability of ANN prediction in the field of different Aluminium MMCs. In addition, this work can also be applied for prediction of measurable parameters in the realm of Physics, Chemistry, Mechanics, Medicine and Metallurgy.ANN can be considered as an alternative way for prediction in various disciplines as it minimizes the cost incurred, human effort, time consumption, miscalculation, and accidents and improves the overall accuracy and efficiency of prediction. The final conclusion is that due to the enhanced capability of ANN, good universal alloy based prediction needs a hybrid ANN.

8. Synopsis

Table 26: Comparative observation of performance of neurons in the hidden layer for load versus wear rate of Al2219 alloy for different weight fraction of reinforcement using different transfer functions

Dataset	No. of Neurons in Hidden Layer	Transfer Function	MSE	Accuracy
As cast Al2219 alloy	10	TANSIG	4.4481E-05	100%
		LOGSIG	4.6953E-05	100%
		PURELIN	1.0600E-02	17.39%
Al2219 +2% TiC	20	TANSIG	5.4094E-05	100%
		LOGSIG	2.0113E-04	76.92%
		PURELIN	1.3533E-03	73.08%
Al2219 +4% TiC	10	TANSIG	5.3593E-05	100%
		LOGSIG	5.0509E-05	95.24%
		PURELIN	8.1705E-05	71.43%
Al2219 +6% TiC	15	TANSIG	4.1977E-05	95.24%
		LOGSIG	7.1336E-05	80.95%
		PURELIN	5.9385E-04	38.10%

Table 27: Comparative observation of performance of neurons in the hidden layer for speed versus wear rate of Al2219 alloy for different weight fraction of reinforcement using different transfer functions

Dataset	No. of Neurons in Hidden Layer	Transfer Function	MSE	Accuracy
As cast Al2219 alloy	10	TANSIG	2.4506E-05	100%
		LOGSIG	3.8445E-05	100%
		PURELIN	7.8960E-04	88.46%
Al2219 +2% TiC	20	TANSIG	3.5164E-05	100%
		LOGSIG	5.1127E-05	100%
		PURELIN	7.8932E-03	22.22%
Al2219 +4% TiC	10	TANSIG	4.1192E-05	100%
		LOGSIG	4.6397E-05	100%
		PURELIN	7.2389E-03	18.52%
Al2219 +6% TiC	5	TANSIG	7.4450E-05	92%
		LOGSIG	7.5337E-05	96%
		PURELIN	16676E-03	28%

9. Statistical report

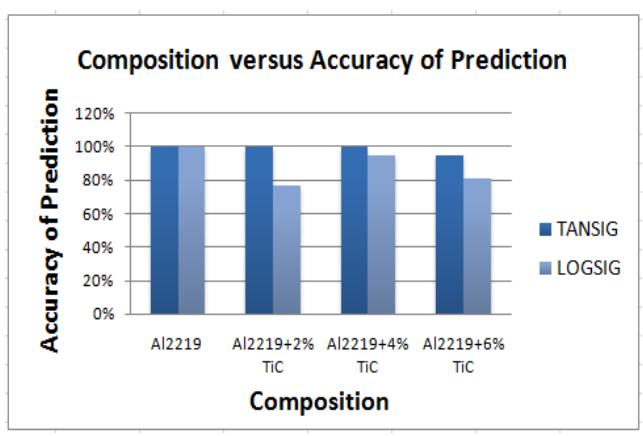

Fig. 45 Statistical analysis for load versus wear rate of Al2219 reinforced with TiC in different weight fractions

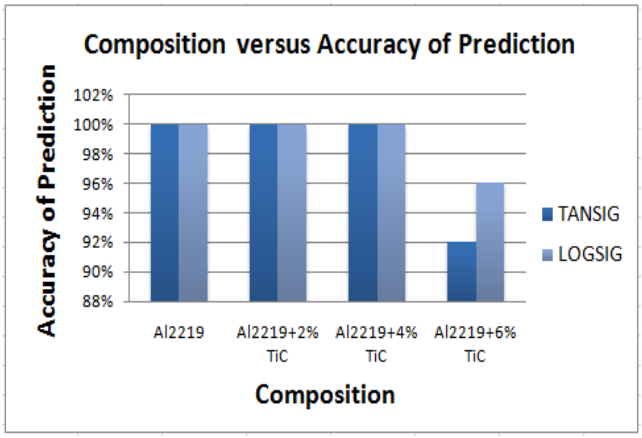

Fig. 46 Statistical analysis for speed versus wear rate of Al2219 reinforced with TiC in different weight fractions

Acknowledgments

We would like to covey our profound gratitude towards the journal, "Wear Behaviour of Al2219-TiC Particulate Metal Matrix Composites" by J.I. Harti, B.R. Sridhar,H.RVitala, & P.R. Jadhav, American Journal of Materials Science,2015, 5(3C), pp. 34-37 which is one of our major data set resource for which this intensive research has become possible.

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