PREDICTION OF FRICTION COEFFICIENT USING ARTIFICIAL NEURAL NETWORK

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Abstract:
In the present study, friction coefficient of fibre reinforced polymeric composites is predicted by developing neural network model as a function of several input parameters, i.e. the sliding distance which is (0-50km), the applied load (30-50-70-100) N and the sliding velocity (2.8-1.1-2.1-3.1-3.5) M/S. Data sets of all the process parameters of the studied Kenaf fibre are received from an experimental study consists of 1096 data for the friction coefficient at different operating parameters. Several models are developed and the optimum is selected which is based on two hidden layers and a training function of GDM, and transfer function of Purelin-Tangsig and 40 neurons. 70% of the experimental data is used for the training purposes and the rest was used for the verification. In the verification, the error percentage was 20%. The prediction was performed for parameters different than the experimental ones and the data is collected and presented. The correlation between the ANN result and the experimental data have been recorded as 0.8195 which reflect only 20% of error.

Key words: Friction coefficient, Artificial Neural Network, GDM training function.

1. INTRODUCTION

It is known that the Mathematical models in research are cannot introduce good correlation with the experimental results because of the complexity of the work. In addition to that, it is consuming a lot of time to estimate such properties in pure mathematical formula.

As alternative, Artificial Neural Network (ANN) has been effective tool to predict many of the tribological properties. ANN is a mathematical model inspired by the biological nerve system. ANN technology is used to solve complex scientific and engineering problems which could be very helpful tool for tribological applications.

The significance of this technology is that ANN models can be trained based on experimental or real life data to recognize solutions. During the training, the ANN model adjusts itself to establish the relation between the cause (input) and consequence (output). The ANN model does not require any clear formula. Instead it is an implicit model, trained to adopt and adjust itself to perform certain tasks.

The ANN technology is best suited in following conditions:

1. A huge database to train
2. Variability or noise in the database, which cannot be recognized in mathematical equations.
3. Nonlinear relation between input and output [1].

2. LITERATURE REVIEW

ANN technology has been efficaciously used to predict the wear behavior of A365/SiC metal matrix composites (mmc) (Rashed and Mahmoud, 2009). That study has confirmed that considerable cost and time could be saved by using ANN technology to predict the outcome. Likewise, ANN model has been developed similar model for metal and silicon carbide MMC(Muthukrishnan and Davim, 2009). Back Propagation model of ANN has been able to predict wear results, with errorof 2.4%. The inputs for the ANN model were the metal and silicon carbide weight percentile, and the test duration. This shows that ANN could be professionally used as a prediction method for composite materials. ANN also has been used for automotive friction materials performance prediction (Aleksendric and Duboka, 2006). Also, another work has been completed on temperature sensitivity of friction material or the fading performance (Papalexopoulos et al., 1994). The fading performance of friction material, regarding the manufacturing condition has been simulated by ANN technic. 360 data have been utilized to train 18 ANN models with 5 verities of training algorithms. The ANN models have predicted the fading performance for unknown variables (manufacturing condition and material property). Relating these input parameters, it has been presented that the developed neural model can be used for predicting the fading performance of the friction materials which composition and manufacturing parameters. Wear loss of Molybdenum coating, which is a strong corrosion resistant, has been studied (Rosen and Silverman, 1992). Mo coating has been applied on ductile iron substrate and the wear rate has been investigated upon environmental plasma spray system. The sliding wear against steel counter body has also been experimented. A double layer ANN model trained with the experimental data has predicted results were reasonably good compared to the experimental results. Used multiple layered back propagation ANN models have been used to predict the friction co-efficient and wear rate of Short fiber reinforced thermoplastics (Bijwe et al., 1989). A well trained ANN model has been capable of predicting the outcome with unknown input parameter with high accuracy.

The ANN is inspired by the biological nervous system and is used to solve a wide variety of complex scientific problems(LiuJie et al., 2007b). ANN technology is used to solve complex scientific and engineering problems (Nasir et al., 2010). The significance of this technology is that ANN models can be trained based on experimental or real life data to recognize solution (Nasir et al., 2010). All the researchers have emphasized that ANN have the ability to predict mechanical properties .The predictive quality of the ANN increased when enlarging the datasets and by optimizing the network construction (LiuJie et al., 2007b).

D. K. Prajapati and M. Tiwari, have used the (ANN) technique to determining surface parameters, friction and wear during pin-on-disc tribotester. The test was performed using pin on disc apparatus under room temperature condition. The pin (25mm long, 6mm diameter) was made of medium carbon steel (AISI 1038) whereas the disc (165mm diameter, 8mm thickness) is made of high carbon steel (SAE 52100). The experimental results obtained from wear testing are compared with those obtained using artificial neural network (ANN) analysis, and a very good agreement in results suggests that a well-trained neural network is capable to predict the parameters in wear process [9].

Chakradhar B. Et al, have presented an experimental investigation and estimation of surface roughness using optimization techniques -Artificial Neural Network (ANN), Group method data handling

(GMDH) and multiple regression analysis (MRA) in high speed micro end milling of titanium alloy (grade-5). They made a comparative study to know the influence of spindle speed, feed and depth of cut on surface roughness of Ti-6Al-4V-titanium alloy. They concluded that prediction accuracy of neural network is higher than other techniques that is in good agreement with experimental values [10].

M. Akbari etal, (2014)used the artificial neural network (ANN) as a model for friction stir welding (FSW), to predict the correlation between FSW parameters and weld properties. They stated that one of the most challenging problems is choosing appropriate welding parameters in order to produce sound joint. They employed different optimization techniques to determine the optimized output parameters by specifying the relation between the input and output variables. They explained the applications of optimization methods in FSW, and basic principles of these methods, such as Taguchi, genetic optimization and multiobjective optimization methods, were described [13].

3. METHODOLOGY

Matlab software was the main equipment used in this research to design the artificial neural network. Generally, basic steps were carried in the methodology as follows:

- Collecting sufficient Tribology data to use in development and training the ANN
- Importing datasets to MATLAB files.
- Building the network.
- Developing the ANN model
- Training the optimal ANN network**.**
- Comparing the experimental and ANN results.
- Make Simulation and prediction for a new tribology data.

3.1 DATA COLLECTION

Large volume of datasets which obtained by experimental work has been used [14]. In previous study, raw Kenaf fibres were studies to investigate the friction coefficient. Composite surface specimens (10 mm × 10 mm × 20 mm) were rubbed against a stainless steel (AISI 304, hardness=1,250 HB, Ra=0.1 µm) counter face under dry/wet contact conditions [14].A feature of a large data is that it gives more accurate results. More than 1000 inputs in relation with more than 300 target have been used to train the network. These various data exported in Microsoft Excel tables to be able used in Matlab software as shown in Fig (1). Input data were the sliding distance, applied force and the velocity while the friction coefficient was the target. Also, the data would be separated into two parts. Firstly, training data set which used in training the network. Secondly, testing data set that used to test the accuracy of network performance in later steps by making a comparison between ANN result and experimental result. It is important to note that the testing dataset is the data which the network has never seen them during the training process.

3.2 IMPORTING DATA IN MATLAB FILES

By choosing Neural Network Tool from MATLAB toolbox, there is an option to import the date from excel file into the workspace of the Matlab.

3.2.1 IMPORTING INPUT TRAINING DATA SET.

Input training imported by clicking on “import” button, where the variables from excel tables will be selected, and this group of variables should be imported as inputs with their own name.

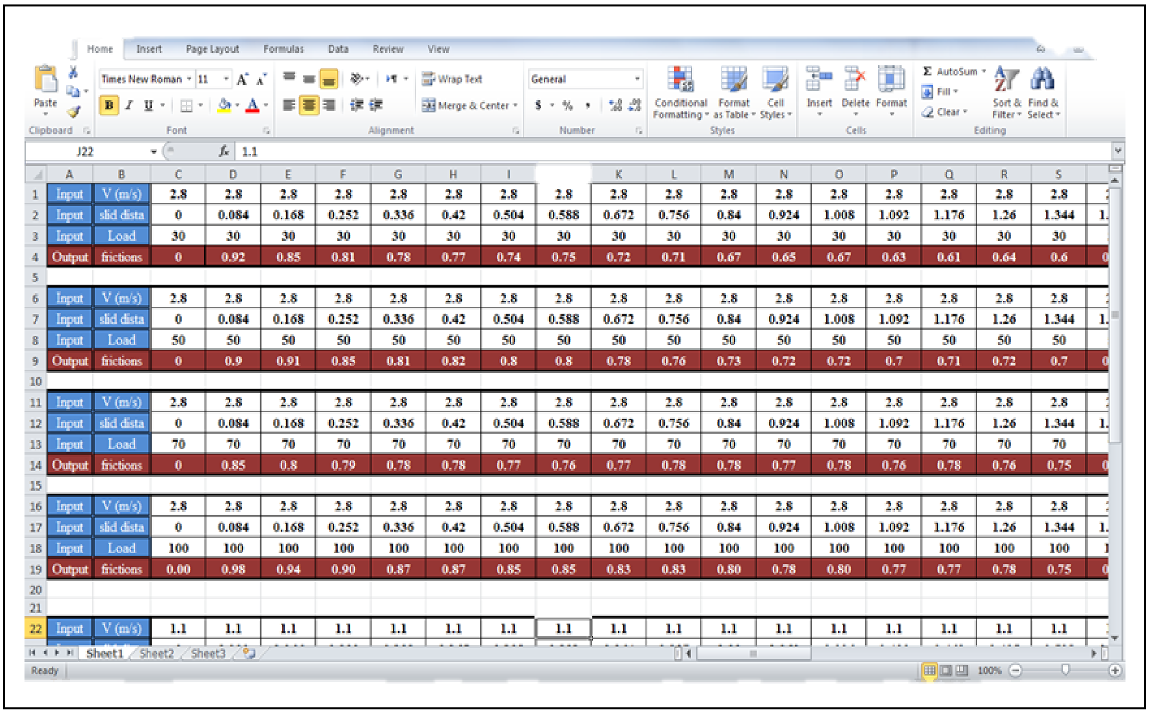
3.2.2 IMPORTING TARGET TRAINING DATA SET

Locating the Training input data by click on "import" button then select the variables from excel tables and this group of variables should be imported as target with their own name. Figure (2) display the network data manager where the target and target data can be imported. Also, show other keys that are used when creating the network.

3.3 BUILDINGTHE NETWORK

3.3.1 CHOOSING THE BEST TRAINING FUNCTION

Training and learning functions are mathematical manner consumed in Matlab to automatically correct the network's weights. Variety of training algorithms, are supported by Neural Network Toolbox. These training functions named GDM, GDA, GDX, LM, OSS, R, RP, and SCG. The objective of the current step is to find the best ANN training function to be used in the ANN developed model. For this reason, all the training functions that available in the Matlab software will be compared. Finally the efficiency of eight different ANN training functions were compared to choose the best function. Table 3.1 shows the configurations of the eight neural network and it can be seen that number of neural were assumed to be 20display in the first layer variety of training.



	A	B	C	D	E	F	G	H	I		K	L	M	N	O	P	Q	R	S
1	Input	V (m/s)	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8
2	Input	slid dista	0	0.084	0.168	0.252	0.336	0.42	0.504	0.588	0.672	0.756	0.84	0.924	1.008	1.092	1.176	1.26	1.344
3	Input	Load	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30
4	Output	frictions	0	0.92	0.85	0.81	0.78	0.77	0.74	0.75	0.72	0.71	0.67	0.65	0.67	0.63	0.61	0.64	0.6
5																			
6	Input	V (m/s)	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8
7	Input	slid dista	0	0.084	0.168	0.252	0.336	0.42	0.504	0.588	0.672	0.756	0.84	0.924	1.008	1.092	1.176	1.26	1.344
8	Input	Load	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50
9	Output	frictions	0	0.9	0.91	0.85	0.81	0.82	0.8	0.8	0.78	0.76	0.73	0.72	0.72	0.7	0.71	0.72	0.7
10																			
11	Input	V (m/s)	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8
12	Input	slid dista	0	0.084	0.168	0.252	0.336	0.42	0.504	0.588	0.672	0.756	0.84	0.924	1.008	1.092	1.176	1.26	1.344
13	Input	Load	70	70	70	70	70	70	70	70	70	70	70	70	70	70	70	70	70
14	Output	frictions	0	0.85	0.8	0.79	0.78	0.78	0.77	0.76	0.77	0.78	0.78	0.77	0.78	0.76	0.78	0.76	0.75
15																			
16	Input	V (m/s)	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8
17	Input	slid dista	0	0.084	0.168	0.252	0.336	0.42	0.504	0.588	0.672	0.756	0.84	0.924	1.008	1.092	1.176	1.26	1.344
18	Input	Load	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
19	Output	frictions	0.00	0.98	0.94	0.90	0.87	0.87	0.85	0.85	0.83	0.83	0.80	0.78	0.80	0.77	0.77	0.78	0.75
20																			
21																			
22	Input	V (m/s)	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1

Fig. 1 Excel tables with three input data and one output

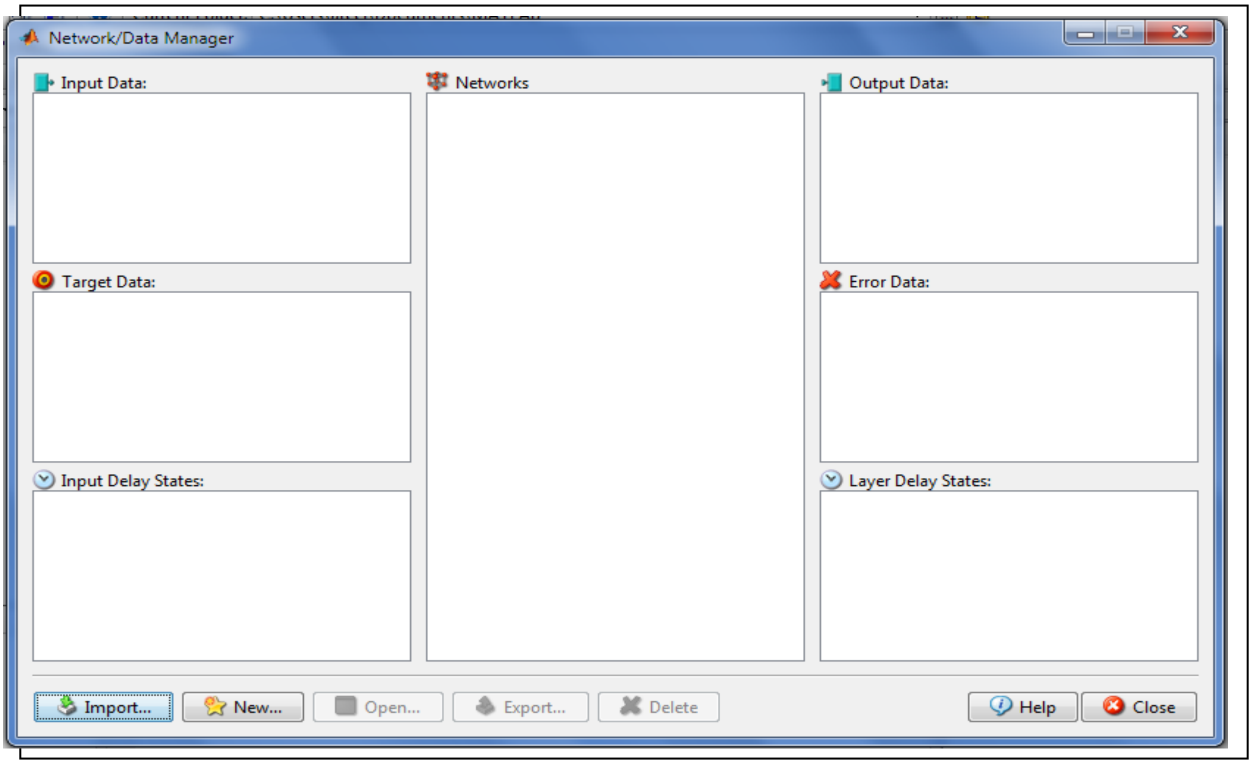


Fig. 2 Print screen of Matlab software

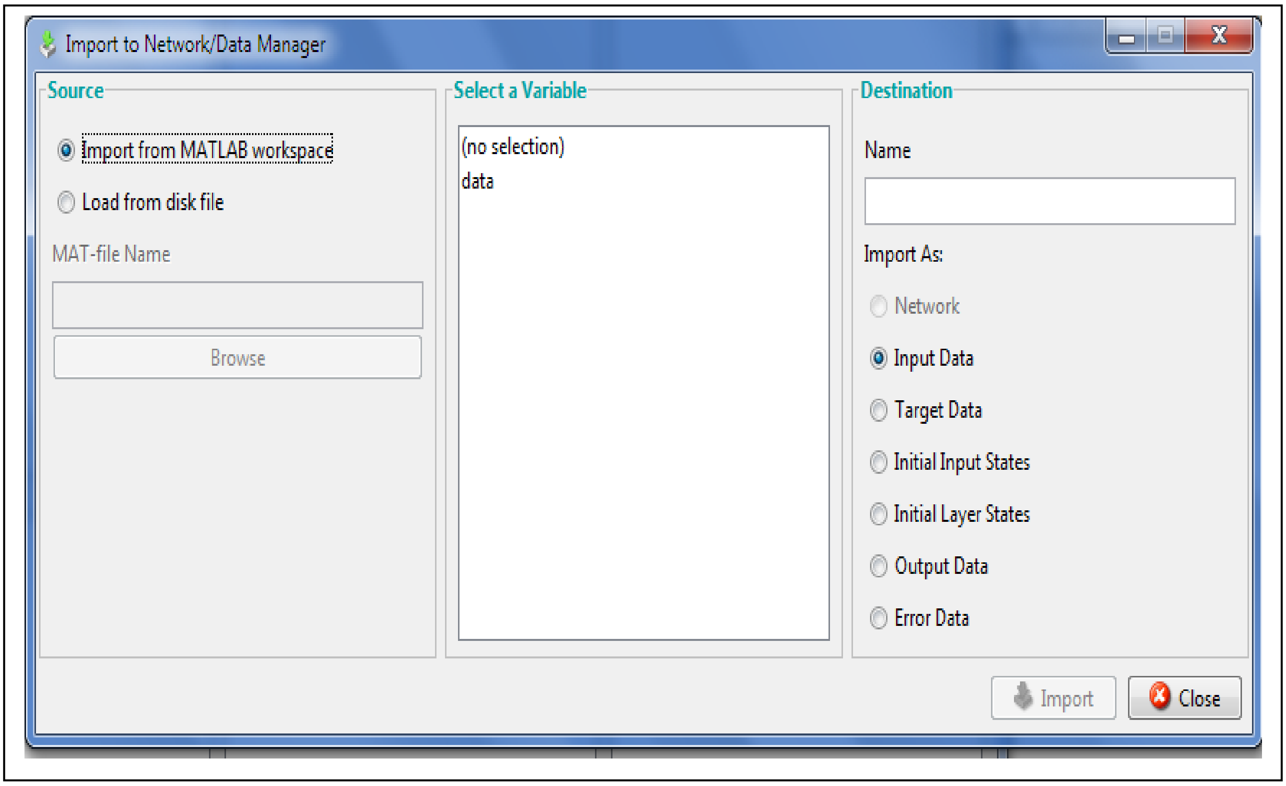


Fig. 3 Print screen of Matlab software.

Table (1) Different neural network configurations by different training functions.

S.N	Function performance	Layer 1	layer 2	Network type
ANN1	GDM-MSE	20	Pure line	Feed-forward backprop
ANN2	GDA-MSE	20	Pure line	Feed-forward backprop
ANN3	GDX-MSE	20	Pure line	Feed-forward backprop
ANN4	LM-MSE	20	Pure line	Feed-forward backprop
ANN5	OSS-MSE	20	Pure line	Feed-forward backprop
ANN6	R-MSE	20	Pure line	Feed-forward backprop
ANN7	RP-MSE	20	Pure line	Feed-forward backprop
ANN8	SCG	20	Pure line	Feed-forward backprop

3.3.2 CHOOSING THE BEST TRANSFER FUNCTION

Matlab software suggests many inbuilt transfer functions such as like logarithmic sigmoid function (logsig), pure linear function (purelin), tangential sigmoid function (tansig)(Kohli and Dixit, 2005).There are three types of transfer functions, linear, sigmoid, and hyperbolic tangent were utilized in this study. The processes of choosing the best function are achieved by trying to mix all different transfer function and then comparing their performance. In the current research, nine different combinations have been tried.

3.3.3 CHOOSING NUMBER OF NEURONS

Selecting the best number of neurons is necessary to reduce the error in both training and testing drops to an acceptable value (Dixit and Chandra, 2003).In order to increase the accuracy two hidden layer were used. Number of hidden layer neurons is increased from three to forty in the first layer. For the selected eight networks configuration, at the end of their individual runs with the same training datasets and Mean square error are compared. The best fitted network is achieved by obtaining the less percentage of rms error.

3.3.4 TRAINING THE OPTIMAL NETWORK

The neural network has used the best configuration model to be ready to start training the network. Figure (4) shows the Matlab screen during the training process and indicates that at the end of the training process, it can get performance, training state and regression plots. In this stage, calculation and statistical results will be plotted to assess the training quality.

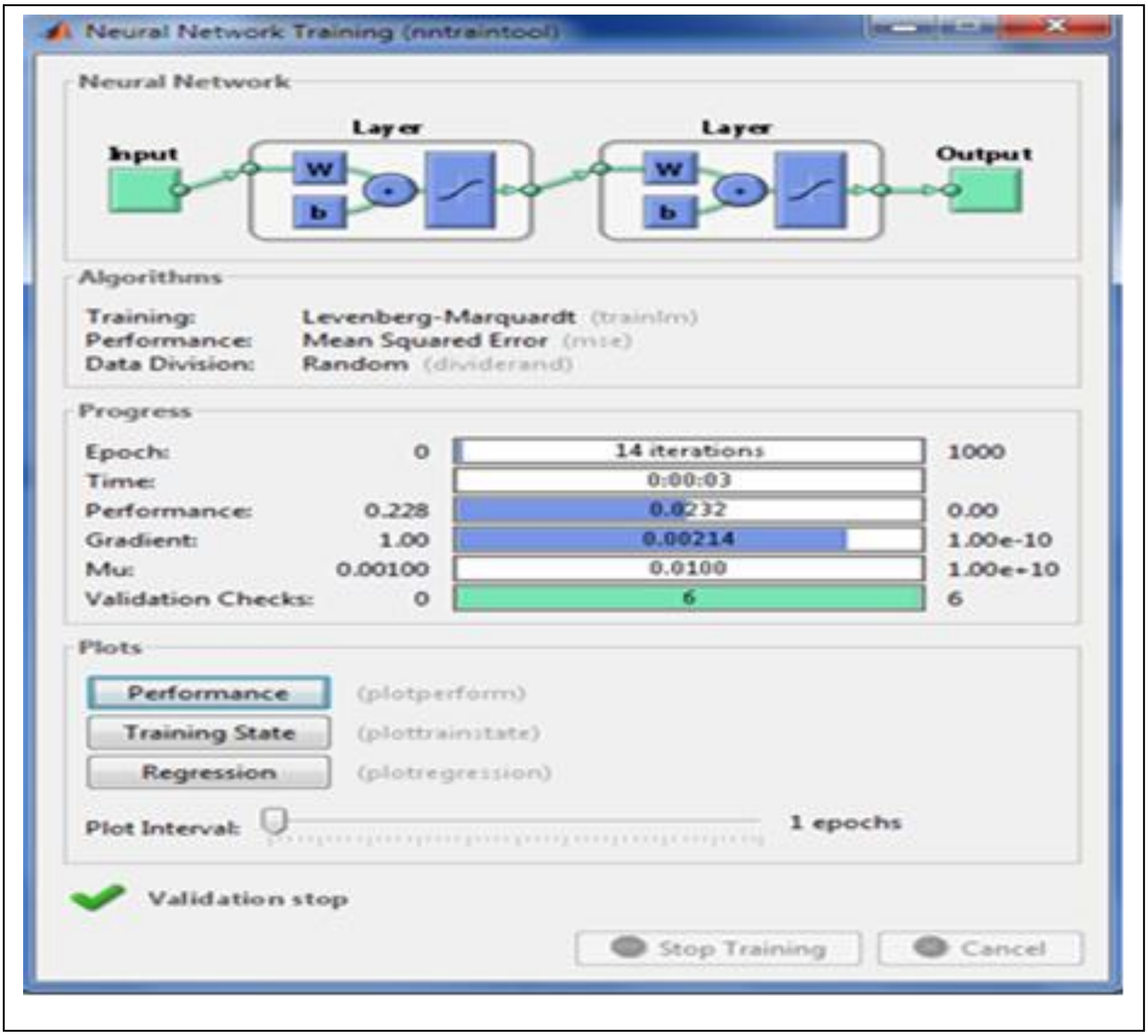


Fig. 4 Neural network apps monitor training progress.

3.3.5 TRAINING THE SELECTED MODEL

Firstly, training the optimum ANN model has been carried. Then, testing the model for importing new input data. ANN developed model, can effectively make predictions and new targets are obtained through this model. The experimental results of these testing data are already defined in Microsoft Excel table. Later, making a comparison between experimental and ANN model will be carried.

3.3.6 SIMULATION AND REDICTION

Neural Network Toolbox offers a set of bottom for building neural networks simulation. At this point the developed ANN ready in use to predict a new data. The selected ANN model is trained with Train GDM function up to 1000 epochs.

4. RESULTS AND DISCUSSION

The data have been collected from previous experimental work. Big volume of experimental data that presented in three input parameters which are applied force, sliding duration and rotation speed in relation with one output which is the friction coefficient. During this investigation ANN developed model has been used to predict the friction coefficient of the CGRP composite in different selection conditions. The neural network method is a powerful approach to make predictions.

For fig (5) the 30N applied load, there is a bit fluctuating in the experimental data that could be occurred from orientation fibre which may has some influence. All figures showing that there is a linear relation of ANN results compared with experimental data and that it could make other problems.

Figures are developed the result to gives a comparisons between the values of friction confection the abstained from the experimental work and the friction coefficient value that obtained from ANN prediction. The following figures are for different seed (1.1, 2.8, 3.1 and 3.5) m/s and different apply load (30, 50, 70, 100) N. From these figures we can find a very good clarification between the experimental and ANN data. However, there are a bit separation differences between them.

4.1 AT 2.8 M/S

For figure (5) the 30N applied load, there is a bit fluctuating in the experimental data that could be resulted from orientation fibre which may has some influence. All figures showing that there is a linear relation of ANN results compared with experimental data and that it could make other problems.

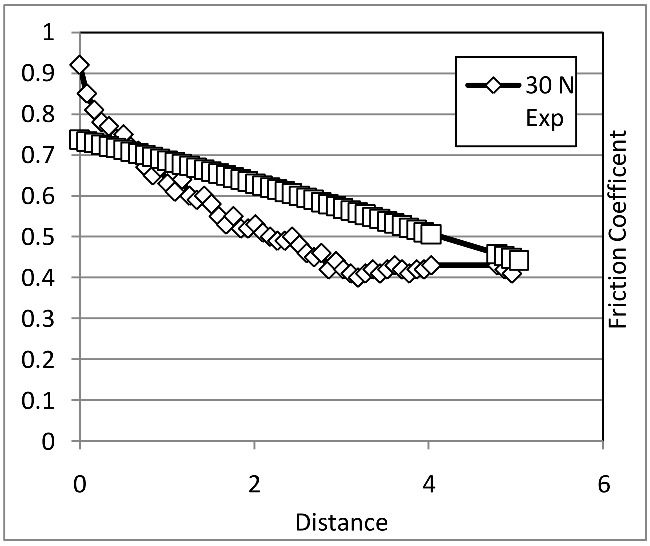


Fig.5 Compassion between experimental data and ANN data at(2.8M/S, 30N).

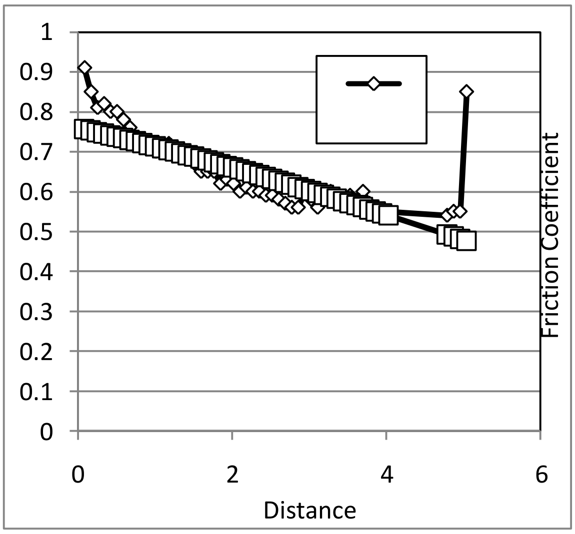


Fig. 6 Compassion between experimental data and ANN data at (2.8M/S 50N).

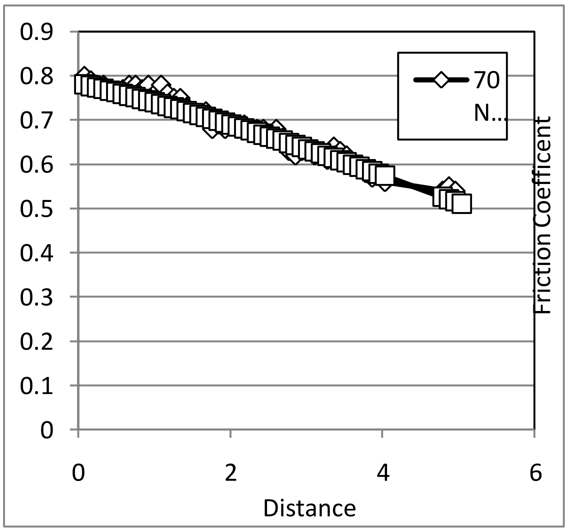


Fig. 7 Compassion between experimental data and ANN data at (2.8M/S 70N).

4.2 AT 1.1 M/S

It can see that figure (9) present a good coloration between the experimental data and ANN result especially with the sliding distance above 0.5km both results are very close to each other.

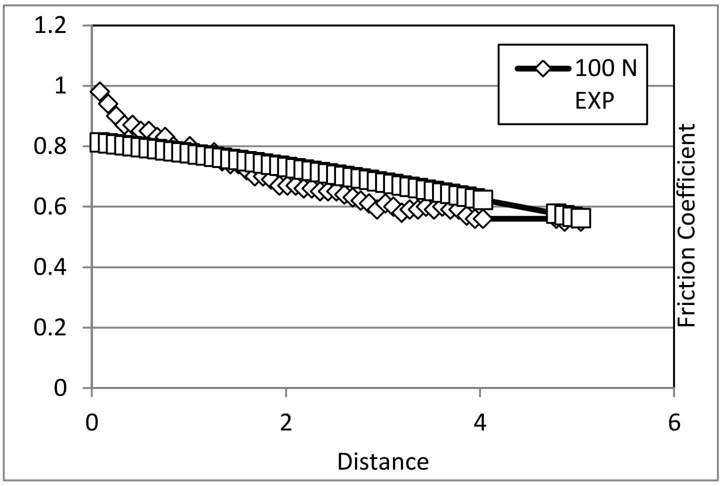


Fig. 8 Compassion between experimental data and ANN data at (2.8M/S 100N).

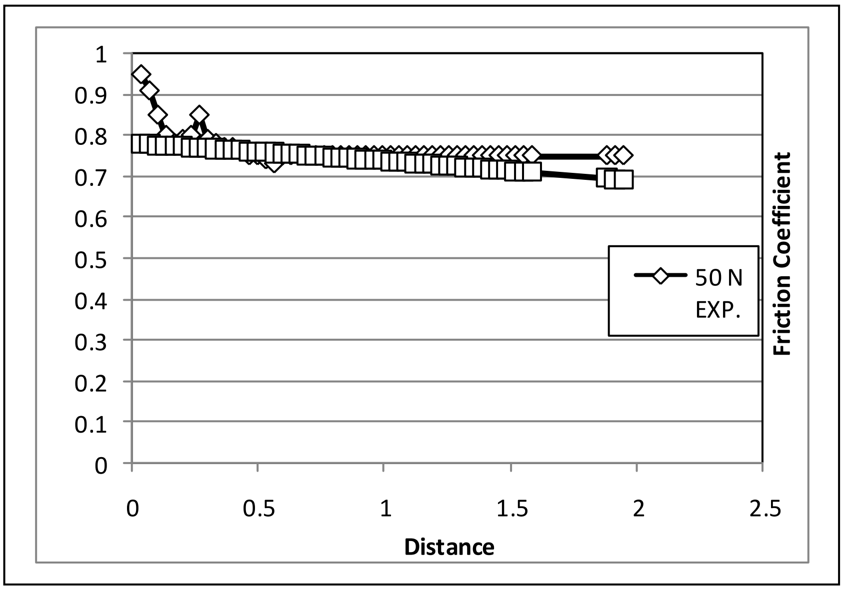


Fig. 9 Compassion between experimental data and ANN data at (1.1M/S,50N).

4.3 AT 3.1 M/S3

Figures (10) present the experimental and ANN data at 3.1 m/s sliding speed and 50N applied force. Figure (11) present the experimental and ANN data the different velocity sliding speed while the applied force is the samewhich is (50N). Both figures actually, do not present a good coloration between the compared results

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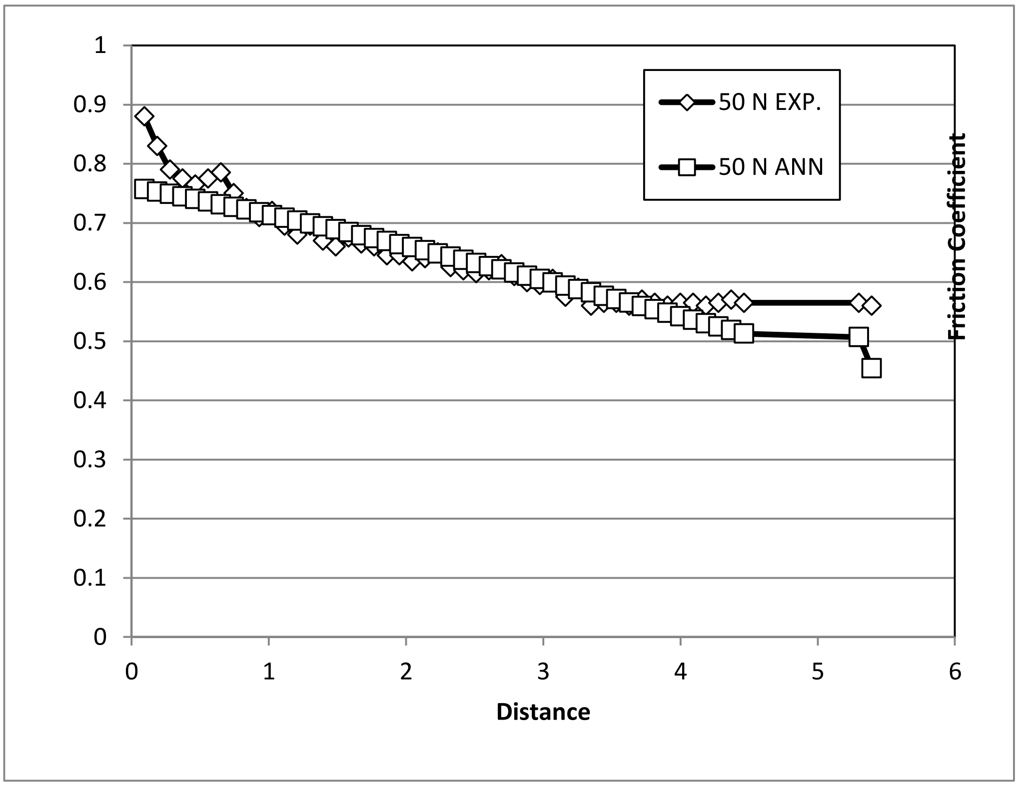

Fig. 10 Compassion between experimental data and ANN data at (3.1M/S, 50N).

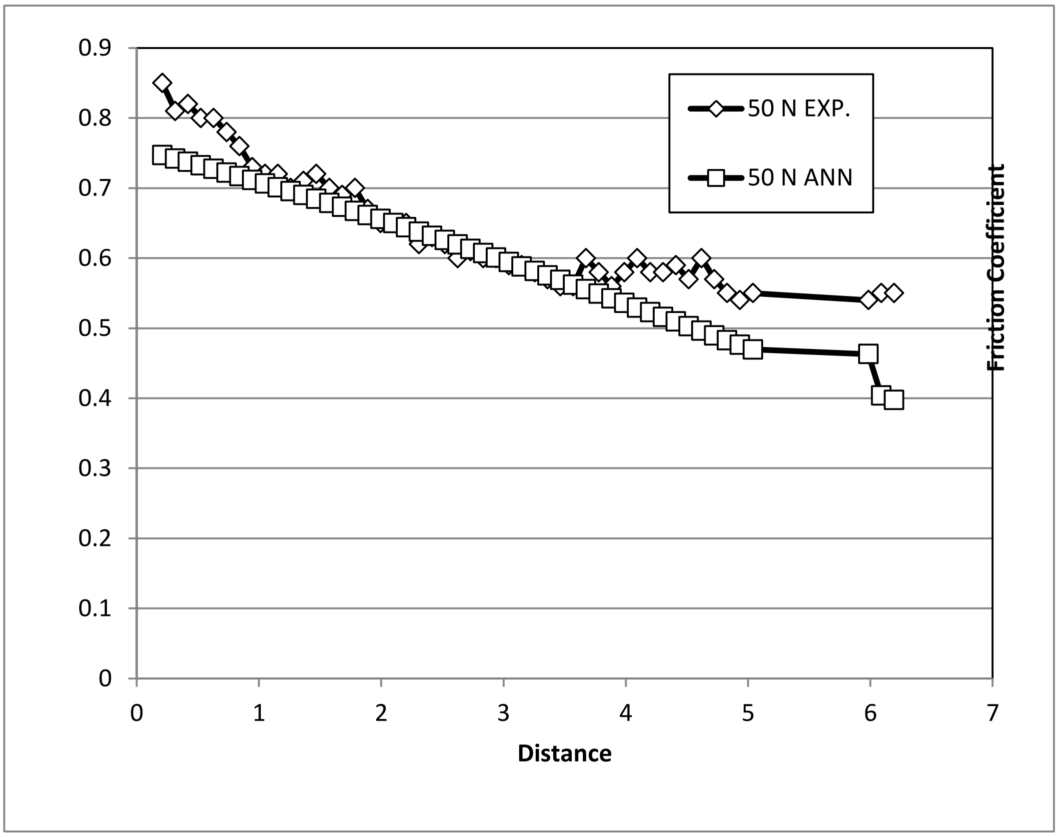

Fig. 11 Compassion between experimental data and ANN data at (3.5M/S, 50N).

5. CONCLUSION

1) ANN technique can be considered as a good technique for predicting friction factor.

2) Applied load, speed and the sliding distance have a considerable effect on the friction coefficient.

3) The developed model showed encouraging result in the prediction of friction coefficient.

4) Good improvement in results was achieved when using Multi-layer ANN models with large number of neurons.

5) The training function showed a significant impact on the ANN performance.

6) Training function of GDM achieved the best performance for the current work.

In general good agreement between ANN results and experimental results.

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