An artificial neural network for prediction of the friction coefficient of multi-layer polymeric composites in three different orientations

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Abstract: In the present work, an artificial neural network (ANN) model was developed to predict frictional performance of a polymeric composite. The experimental dataset at different applied loads (30–100 N), sliding speeds (300–700 r/min), and up to 10 min of sliding duration was used to train the model. The ANN model was trained with a large volume of experimental data (7389 sets). In addition to that, fibre mat orientation was considered in ANN development. Various configurations with different functions of training were used to find the optimal model. As a result of this work, single-layered models with large number of neurons showed high accuracy, up to 90 per cent in prediction, when trained with the Levenberg–Marqurdt function.

Keywords: artificial neural network, friction coefficient, multi-layer composites

1 INTRODUCTION

Tribological properties of polymeric composites are strongly influenced by many operating parameters and contact conditions [**1–3**]. Mathematical models for their study did not show good correlation with experimental results. In addition to that, to estimate such properties using pure mathematical formulae is time-consuming. As an alternative, artificial neural networks (ANN) have been a successful tool for predicting some tribological properties [**4**, **5**]. ANN is a mathematical model inspired by the biological nervous system. ANN technology is used to solve complex scientific and engineering problems. The significance of this technology is that ANN models can be trained based on experimental or real life data to recognize solutions.

The ANN prediction method has been used in several applications [**4–16**], such as wear [**4–7**, **14**, **16**], friction [**4**, **5**, **12**, **16**], solid particle erosion [**9**, **10**], temperature sensitivity [**8**, **13**], and surface roughness [**11**]. All of the reported works found that ANN is able to predict the output parameters to different levels of accuracy. However, there are a few elements that control the ANN performance, i.e. training function [**4–16**], input data [**4**, **5**, **10**, **12**, **13**, **16**], and the number of hidden layers [**4**, **5**, **9**, **12**, **13**]. For instance, in reference [**12**] and [**13**], it has been found that a larger training database provides higher accuracy of ANN. However, in reference [**10**], the prediction was limited due to a large number of input variables. For the training function, it has been found that Bayesian Regularisation (TrainBR) and Levenberg–Marquardt (TrainLM) training function generates an accuracy of up to 0.9 (90 per cent). TrainLM has been the optimal training function for reference [**8**] with 0.9762–0.9795 performances. However, in reference [**5**], the CGB and GDX training function performed well, providing 0.9–1.0 performance. Regarding the layer configuration, it has been found that the layer and neuron number are dictated by the nature of the input data. In reference [**4**] the input parameters were 9, therefore the hidden layer was 3. While in reference [**14**], the input parameters were only 2, and the hidden layer was only 1. In other words, it was found in the previous works that the number of hidden layers and their volume depend on the complexity of the system, i.e. number of input parameters, data fluctuations, and irregularities.

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ANN technology has been used successfully to predict the wear behaviour of A365/SiC metal matrix composites (MMC) [**6**]. In that work, wear influencing parameters have been SiC particle size, SiC weight percentage applied pressure, and testing temperature on the wear resistance, etc. That work has proven that considerable cost and time could be saved by using ANN technology to predict the outcome. Similarly, ANN models have been developed using a similar model for metal and silicon carbide MMC [**7**]. A back propagation model of ANN has been able to predict wear results, with an absolute relative error of 2.4 per cent. The inputs for the ANN model were the metal and silicon carbide weight percentile, and the test duration. This indicates that ANN could be efficiently used as the prediction technique for composite materials. The ANN approach to predicting the rise of contact temperature in two sliding bodies has been performed [**8**]. Mating surface roughness and testing conditions, load and sliding velocity have been used as the influencing input parameters. A multi-layered back propogation model with a Lavenberg–Marquardt algorithm ANN has been used for the prediction. The correlation between the predicted result and the experimental data has been 0.9762 (contact surface) 0.9795 (temperature). The prediction ability has been maintained even with variation in the input parameters. In another work, ANN was applied to predict solid particle erosion in polyphenylene sulphide (PPS) [**9**]. Impact velocities, impact angle of sand or silica, ratio of glass fibre, and PPS have been the variables for the experiments. The ANN predictability of erosion was in the acceptable range. A three-layer neural network was optimized to perform the prediction task. In another ANN application, the erosion or micro-abrasion between a polymer–steel couple and a ceramic–lasercarb coating couple was experimented [**10**]. Although the modelling and training of multi-layered ANN have produced encouraging results, ANN application scope has been found to be limited, because of the large number of input variables. The relation between the roughness parameter and real area of contact has been studied [**11**]. Optical profilometers have been used to generate 2D profiles of surfaces. ANN has been applied to determine the complex relation between the two variables. A trained ANN model has been able to formulate the relation for unseen (untrained) surface parameters as well. Skewness and kurtosis have been found to be the least influencing parameter for ANN. This application provided strong evidence of ANN's computational ability and for identification of a minimal set of input parameters analysing the contributions of the input parameters. ANN has also been used for automotive friction materials performance prediction [**12**]. The friction performance before and after have been recorded. In that work, ANN has been used to predict the brake factor C, against 26 input parameters. Fifteen different ANN models trained with five different algorithms have been trained and tested. The results demonstrated incredible prediction capability of ANN technology, even with a large number of input parameters (26). Similarly, another work has been carried out on the temperature sensitivity of friction material or the fading performance [**13**]. The fading performance of friction material, regarding the material property and manufacturing condition, has been simulated by ANN technology. A total of 360 sets of data have been used to train 18 ANN models with five different training algorithms. The ANN models have predicted the fading performance for unknown variables (manufacturing condition and material property). Regarding these input parameters, it has been shown that the developed neural model can be used for predicting the fading performance of the friction materials with composition and manufacturing parameters. Wear loss of molybdenum coating [**14**] has been predicted by a double-layer ANN model trained with the experimental data and it was reasonably well compared. Multiple-layered back propagation ANN models have been used to predict the friction coefficient and wear rate of short fibre reinforced thermoplastics [**4**]. A well-trained ANN model has been capable of predicting the outcome with unknown input parameters with high accuracy.

In view of the above, it is evident that the ANN technology can be utilized in predicting the outcome of various tribological tests. The ability to solve complex non-linear problems is an outstanding merit of ANN. Tribological properties are influenced by complex and microscopic phenomenon. The unique learning capability of ANN makes it a viable tool for tribological predictions. Less work has been carried out to study the adhesive friction performance of multi-layer polymeric composites. A properly executed ANN technology could help the study on chopped strand mat glass reinforced polymeric composite (CGRP). Accordingly, the current work initiated a study of the friction performance of CGRP composite under dry contact conditions considering three different orientations. The experimental tests were carried out previously against polished stainless-steel counterface using a newly developed machine for different test durations (5–30 min) at different applied loads (30–100 N) and rotational speeds (300, 500, 700 r/min) [**2**]. ANN operations were conducted using the MATLAB Neural Network Toolbox.

2 EXPERIMENTAL WORKS

2.1 Material preparation and test specimen

Material and composite preparation were described previously [**2**]. The reinforcing material was chopped strand mat of glass fibres (CSM). CSM had 20–30 mm fibre length with 450 g/m^2 mass of fibres. The orthophalic unsaturated polyester resin (Revesol P9509) was pre-promoted for ambient temperature cure, and cured with the addition of methyl ethyl ketone peroxide as a catalyst. In fabricating chopped strand mat glass fibre reinforced thermosetting polyester (CGRP) composite, a smooth wooden mold was coated with a light layer of liquid polyvinyl acetate as a release agent. A paint roller soaked with polyester resin rolled over the mold surface to make the first layer of polyester resin, followed up by a sheet of CSM was laid over the first layer of the polyester resin. Entrapped air between the layers was squeezed out, during the build-up process, using a smooth steel roller, which also ensured that the polyester resin layers are distributed uniformly over the surfaces. Another layer of polyester resin was applied over the glass fibre sheet. Repeating the same process, glass chopped reinforced polyester were built up to a thickness of 15 mm, and consisted of 13 layers of CSM glass fibres. Then the material was cured under room temperature conditions for 24 h. A sample of the composite surface fibre orientations with respect to the siding direction is shown in Figs 1 and 2, respectively. The orientations of the composite are determined by the orientation of the CSM with respect to the sliding direction as parallel, anti-parallel, and normal. In the parallel orientation (P-O), the CSMs are parallel to the sliding direction and applied load (Fig 2). In the case of anti-parallel orientation (AP-O), the CSMs are perpendicular to the sliding direction and parallel to the applied load. On the other hand, normal orientation (N-O) defines when the applied load is normal to the CSMs.

2.2 Wear and friction tests

The fabricated CGRP composite material was machined to 11 mm × 11 mm × 15 mm and the sliding was performed on an 11×11 mm^2 face. The CGRP orientations are shown in Fig. 2. A block-on-ring tribological test machine was used for the friction tests (Fig. 3). The counterface was made of stainless steel (AISI 304, 50 BH hardness and 0.09 μm Ra roughness) with 170 mm diameter and 6 mm thickness. The surface was grinded and polished with abrasive paper (diamond brand water proof, no-120). The tests were conducted under dry conditions at ambient temperature with various normal loads (30, 50, 70, 100 N), rotational speeds (300, 500, 700 r/min), and sliding durations (0–600 s). The tests were repeated for three fibre orientations with respect to the sliding direction, i.e. parallel (P), anti-parallel (AP), and normal (N) (Fig. 2). The frictional force at the sliding interface of the specimen was monitored and captured every 3 s. A load cell placed on the lever holding the specimen converted the strain data to friction force data. Further details of the experiment are given in the previous work [**2**].

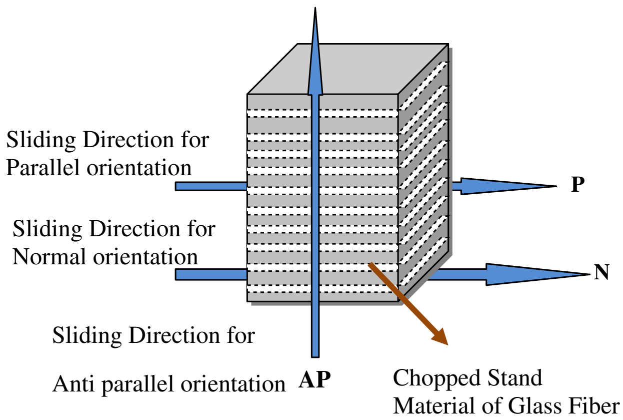

Fig. 2 Schematic illustration of CGRP, specimens showing the orientation with respect to the sliding direction

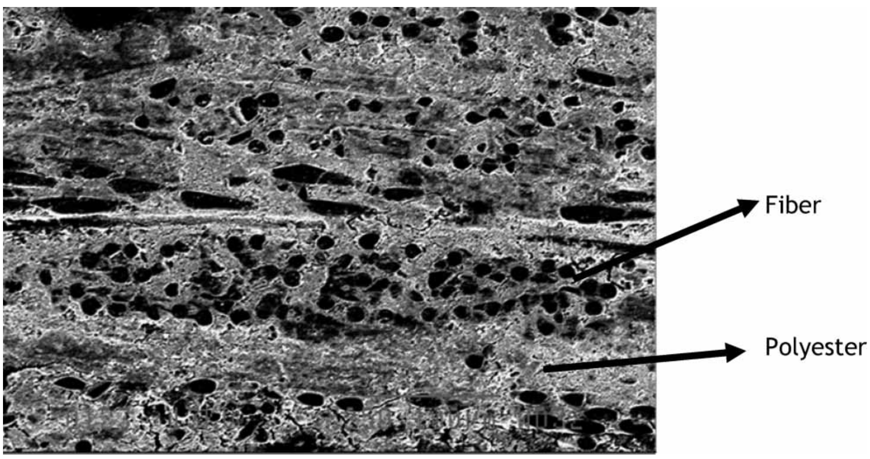

Fig. 1 SEM picture of a cross-section of the virgin material showing the thickness of the polyester interlayers

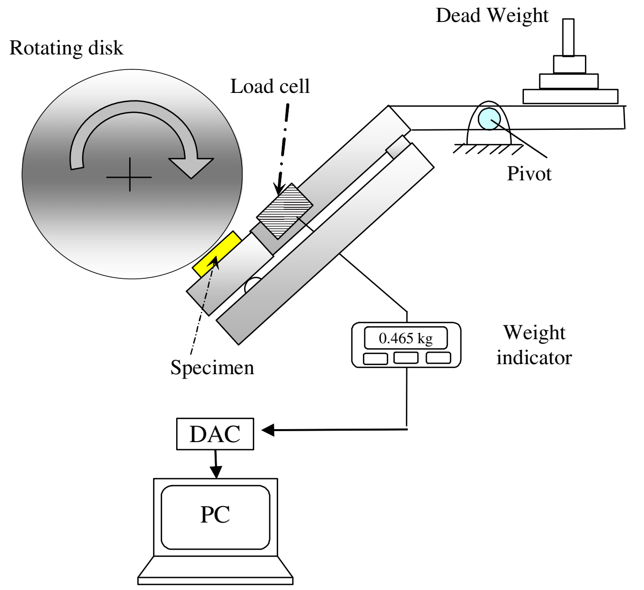

Fig. 3 Layout of the experimental set-up for measuring the friction

3 DEVELOPMENT OF ANN MODELS

3.1 General configuration of artificial neural networks

ANN is simply interconnections of many neurons. Figure 4 illustrates the layout of an ANN model. The neurons are arranged in three layers. First is the input layer, where the input dataset is presented; second the hidden layer(s), which is the brain of the system; and finally the output layer, which dictates the outcome of the system. The system maintains an orchestral flow of signals, starting from the input layer, spreading on to the hidden layers and then summing up to the output layer. During the process, the neurons and their interconnections manipulate the input data in each step to finally produce the output. Figure 4 shows there can be one or more layers of hidden neurons. Different types of database and their characteristics require different types of layer configuration. Similarly, the number of neurons in each layer also varies upon the application. It is a method to find out the best suited neural network for a given situation. However, the input and output layer's neuron depends on the number of input and output parameters. For example, for three inputs (force, temperature, and speed) and one output (wear rate) there should be three input neurons and one output neuron.

An ANN model expressed as 4-[10-8]-2 indicates four neurons in the input layer, 10 neurons in the first hidden layer, eight neurons in the second hidden layer, and two neurons in the output layer. The bracket enclosed portion represents the hidden layers.

Each neuron transfers the data or signal to the next neuron, which is manipulated by the 'transfer function' and 'weight' and 'bias' embedded in the neuron. The three elements 'transfer function' [**15**], 'weight', and 'bias' can be described in the following equation

$$X_j^{(n)} = f\left\{\sum_i W_{ij}^{(n)} X_i^{(n-1)}\right\} + b \qquad (1)$$

f is the transfer function, $W_{ij}^{(n)}$ is the weight of node i of the previous layer $(n-1)$ to the current layer (n), $X_i^{(n-1)}$ is the output of the previous layer's $(n-1)$ neuron (j), $X_j^{(n)}$ is the current neuron (nth layer) output. b is the bias.

Hence, the previous neurons output is multiplied by the weight then manipulated by the function and deviated by the bias. During training session, the system changes and adjusts the weight and bias only to optimize performance. The performance is measured by the sum squared error (SSE) value, E [**4**].

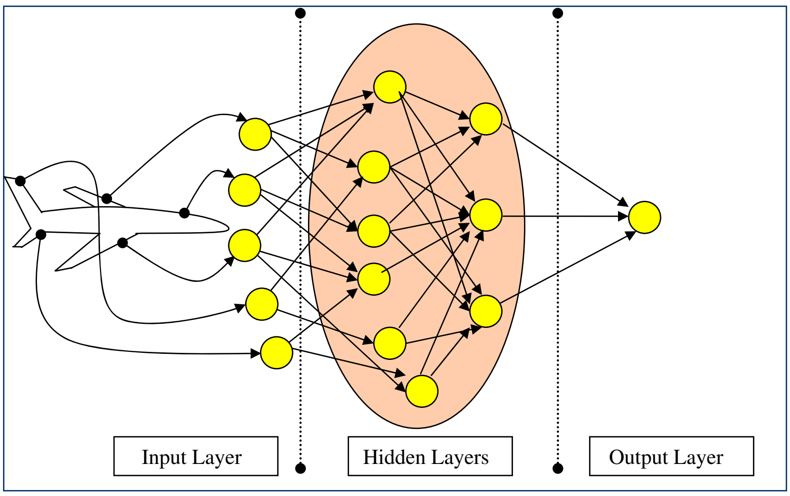

Fig. 4 Artificial neural network configuration

Higher performance ensures less error or high accuracy between input and output

$$E = \frac{1}{2}\sum_{n=0}^{n}(O_i - A_i)^2 \quad (2)$$

O is the experimental or original output and A is the output generated by the ANN model for n number of total datasets.

3.2 Developing the ANN model

For the current study, the ANN was developed in a systematic manner. The work started by collecting and processing the previous experimental data, followed by a series of attempts to come up with an optimal neural model. Finally, the model was trained and tested to simulate the prediction of the friction coefficient. Figure 5 describes the procedure for finding the optimal solution. The detailed steps are explained in the following sections.

3.2.1 Collecting and processing data

Chopped strand mat glass fibre reinforced polymer (CGRP): the experimental data were obtained by previous experimental works [**2**]. The ANN is used to predict the friction coefficient (output) as related to the conditions of the CGRP (input). The input parameters for the current work are fibre orientation, applied force, rotational speed, and sliding duration.

There is a large volume of experimental data. The total set of data is more than 7000 data points. This kind of large data is usually preferable for ANN applications [**5**]. These datasets were converted into MATLAB matrix files, which is used to train various developed ANN models.

3.2.2 Generating optimal ANN model

After processing the collected data, neural network models were developed to predict the friction coefficient. The process was a simple series of attempts with various 'neural' configurations, 'layer' configuration, and the 'function' configuration. By comparing the performance of the developed sample models, an optimal ANN model is developed. The successful model is illustrated in Fig. 6. The network is a three-layer ANN model, with only one hidden layer, i.e. a single-layer ANN model. The hidden layer for this model consists of 40 nodes (neurons).

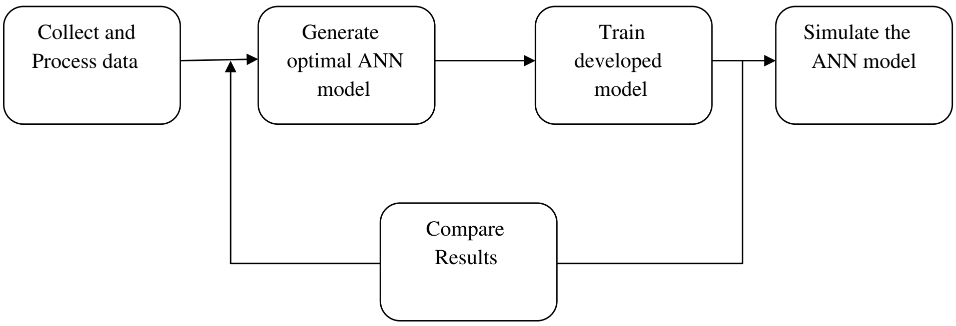

Fig. 5 Flowchart for developing the ANN model

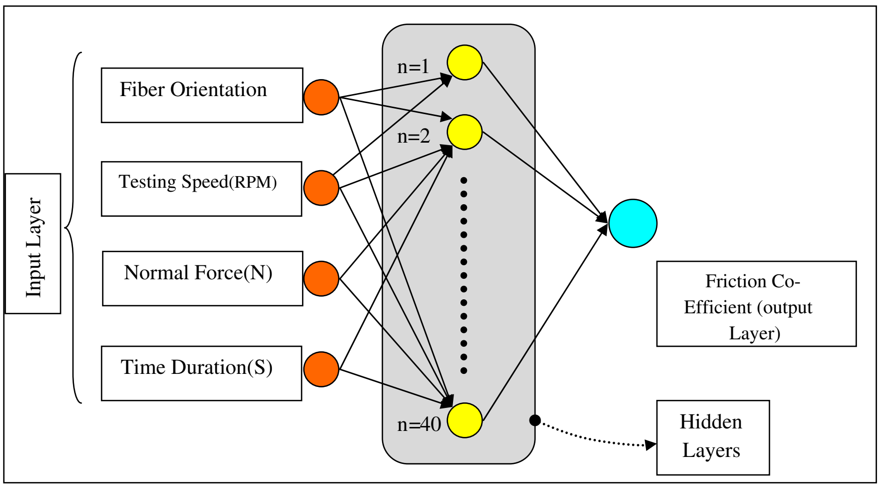

Fig. 6 Schematic of the selected ANN model

3.2.2.1 Selecting the transfer functions. The Matlab ANN toolbox is equipped with three transfer functions: tan-sigmoid, log-sigmoid, and purelinear. Tan-sigmoid and log-sigmoid are functions that can generate outputs of either '0' or '1', whereas purelinear can produce any numerical values, e.g. integers, fractions, −ve, and +ve [**15**]. The transfer function in the first layer (input to hidden) was tan-sigmoid, and in the second layer (hidden to output) was purelinear. In the process of ANN development, it was found that the tan-sigmoid function in the hidden layers generated higher performance compared to log-sigmoid and purelinear. Purelinear in the hidden layer generates an 'error' in the output results. On the other hand, as the output of the system (friction coefficient) can be any numerical value, so pure-linear function must be used in the output layer. Otherwise, the friction coefficient result for CGRP will be only 1 or 0. The performance comparison of transfer functions in the hidden layer is shown in Fig. 7.

3.2.2.2 Selecting the training functions. Training is the process when the ANN compares the experimental output and input, and adjusts the 'weight' and 'bias' of the neurons to achieve closer results. These training functions dictate the adaptation process of the ANN model while it is being trained. For the selected ANN model, {4-[40]-1} Levenberg–Marquardt algorithm (TrainLM) was used to train the network. TrainLM provided the highest accuracy in prediction. A comparison between different training functions is indicated in Fig. 8.

TrainLM showed improvement in performance as the training session was repeated. In Fig. 9, the training performance is displayed. The performance curve is gradually converging towards 0 with epochs. Performance towards '0' indicates the mean less error percentile, and thus higher performance. Epochs are the number of times an ANN model is allowed to adjust the weight and bias to achieve better simulation. As shown in the diagram, 100 epoch means the TrainLM function adjusted the neural weights and biases 100 times as the performance curve converges towards 0.

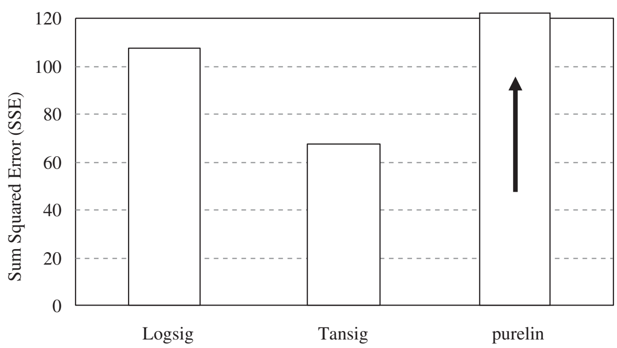

Fig. 7 Comparison of transfer function performance in hidden layers

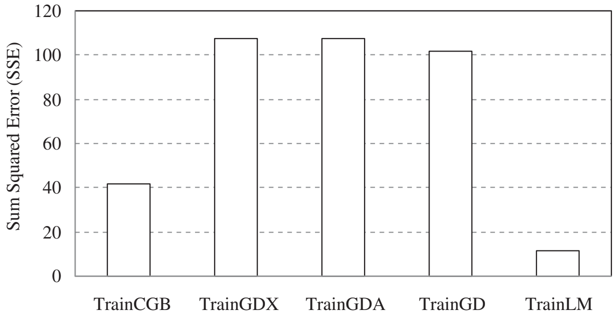

Fig. 8 Comparison of performace after 300 epochs with different training functions

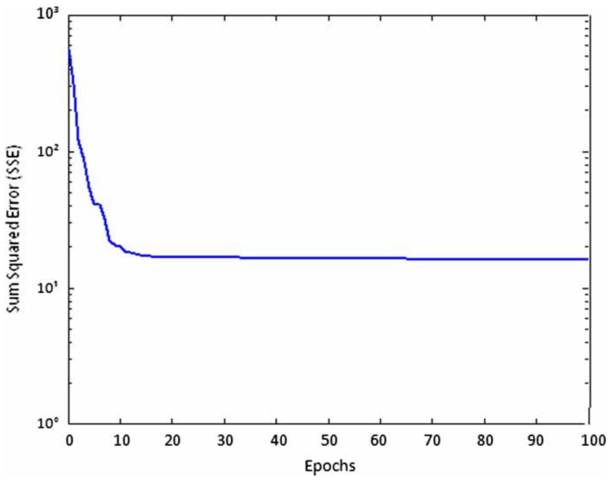

Fig. 9 Training session of 100 epochs for 4-[40]-1 ANN model by TrainLM

Various types of training functions were implemented and tested. They showed distinctive characteristics on the training performance. The summary of these training functions are compared in Table 1.

3.2.2.3 Selecting the layer configuration. Different layers and neuron configurations provide different performances. Various types of neural network model are created and tested to determine the optimal ANN model. The models are trained up to 300 epochs with the training data. The single-layer models showed better performance in the training than the multiple-layer models (Fig. 10). Also the larger single-layer models were comparatively better than the smaller models; e.g. 4-[15]-1. The performance improvement saturated as the hidden layer size exceeded 40 neurons (Fig. 11). The selected ANN model is a single-layer model, with 40 neurons in the single hidden layer.

3.2.3 *Training and testing the selected model*

ANN models improve their performance with repetition of the training process [**3**, **5**]. As the number

Table 1 Summary of training function performance

Training functions	Remarks
(TrainGDX) Gradient descent with momentum and adaptive learning rule	Very high error percentile. No improvement if training repeated. Very fast convergence
(TrainGD) Gradient descent	Similar performance as TRAINGDX. Fast convergence and no improvement with repetition of the training
(TrainCGB) Powell–Beale conjugate gradient	Slower convergence, lower error percentile (higher performance) than TrainGDX, TrainGD. Performance improves with repetition of training
(TrainSCG) Scaled conjugate gradient	Fast convergence, low performance
TrainLM Levenberg–Marquardt	Slowest convergence, highest performance. Significant improvement on repetition of training with same dataset
(TrainGDA) Gradient descent with adaptive learning rule	Fast convergence, low performance

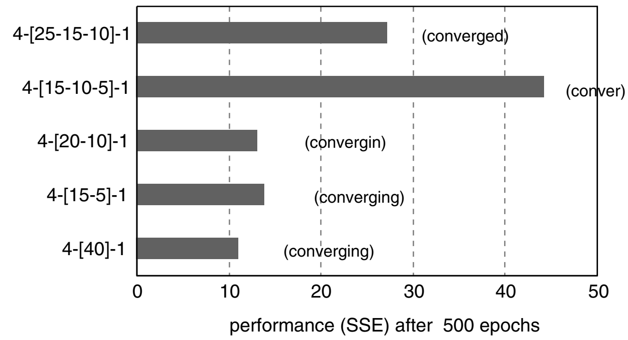

Fig. 10 Performance of multi-layer ANN models after 500 epochs

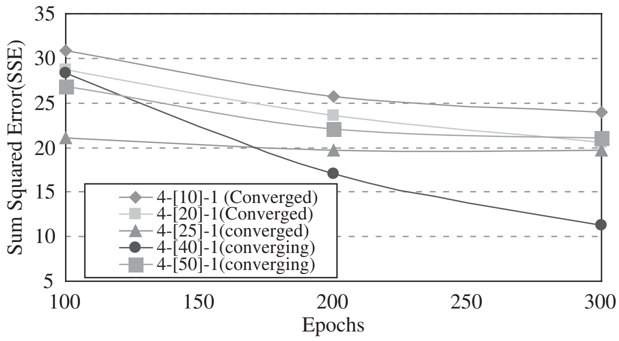

Fig. 11 Performance of various volume single-layer ANN models

of training cycles is increased, an ANN model accumulates the improvement from the previous sessions, and adjusts itself for higher accuracy. The selected ANN model is trained with TrainLM function up to 3000 epochs. In the process the system gradually converged, and no further improvement in performance was observed. Figure 12 shows the training graph of a 4-[40]-1 neural network. The error percentile drops sharply as the training cycles. And it saturates gradually at the 6.8 SSE value. The standard deviation (SD) between experimental and ANN for the friction coefficient is 0.090 304 after the improvement has converged.

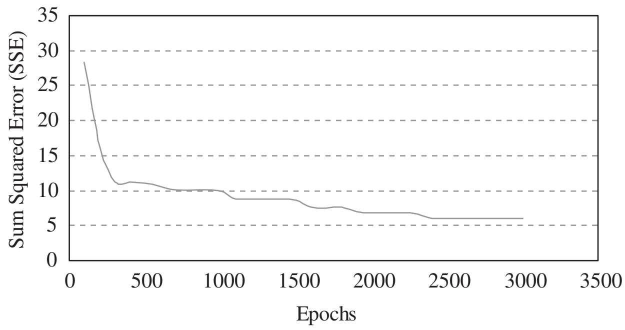

Fig. 12 Training session of the selected ANN model with TrainLM

4 RESULTS AND DISCUSSION

4.1 Comparison of experimental and ANN results

Experimental and ANN frictional results of CGRP composite, tested in three different orientations at different applied loads (30–100 N) and sliding speeds (300–70 r/min), for different test durations (0–600 s) are obtained. The figures were in large volume (36 figures). Samples of the results are displayed in Figs 13–15 showing the correlation between the experimental and ANN results of the CGRP composite in different orientations. In general, one can see a good relation between the prediction and experimental results for all the tested parameters and fibre orientations. It should be mentioned here that the friction coefficient values of the CGRP composite did not show steady state during the tests [**2**]. In spite of that, a close trend of ANN and experimental results can be seen especially for the composite in AP-O and P-O (Figs 14 and 15), respectively. However, there is a slight difference in the ANN results compared to the experimental one of the CGRP in N-O (Fig. 14). From the experimental works [**2**], the friction coefficient of the composite in N-O was not stable during the test. This was due to the frequent changes in the contact of the asperities. In other words, sliding in this orientation leads to either a layer of polyester or glass mat which is in contact with the counterface. This makes the experimental

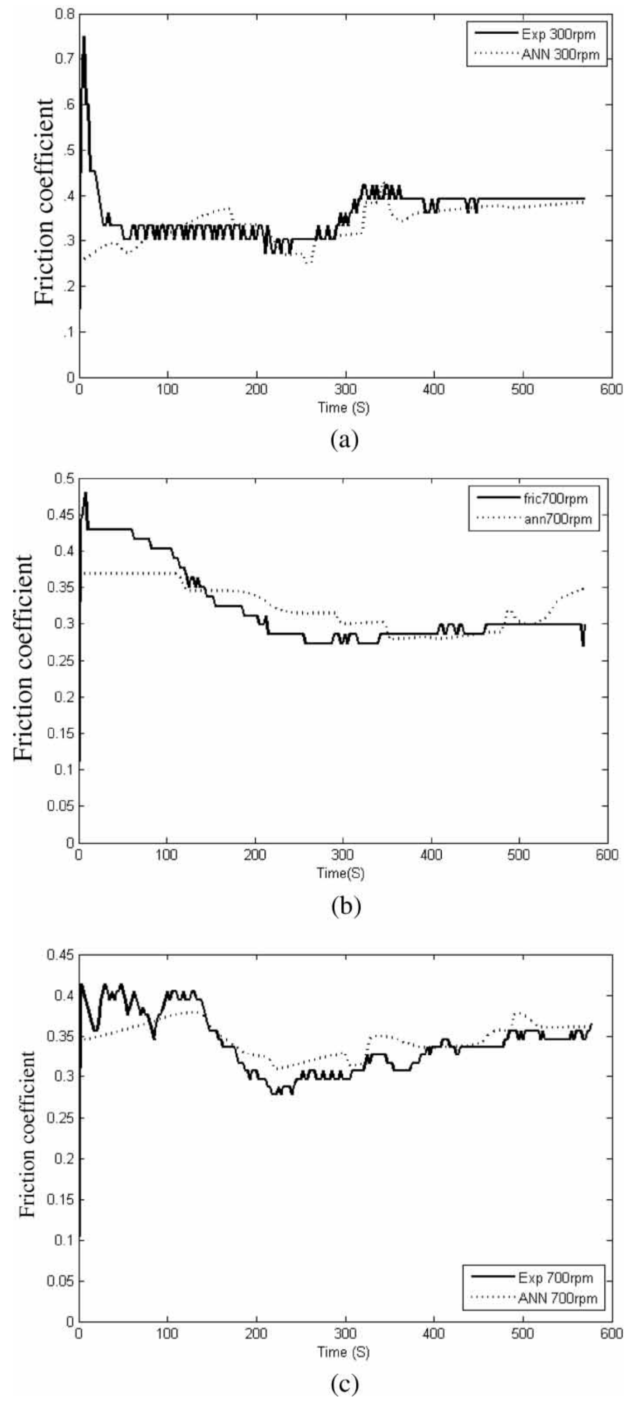

Fig. 13 Experimental and ANN friction coefficient results at different parameters of CGRP composites in N-O: (a) N-O at 30N applied force at 300 r/min; (b) N-O at 50N applied force at 500 r/min; and (c) N-O at 70N applied force at 700 r/min

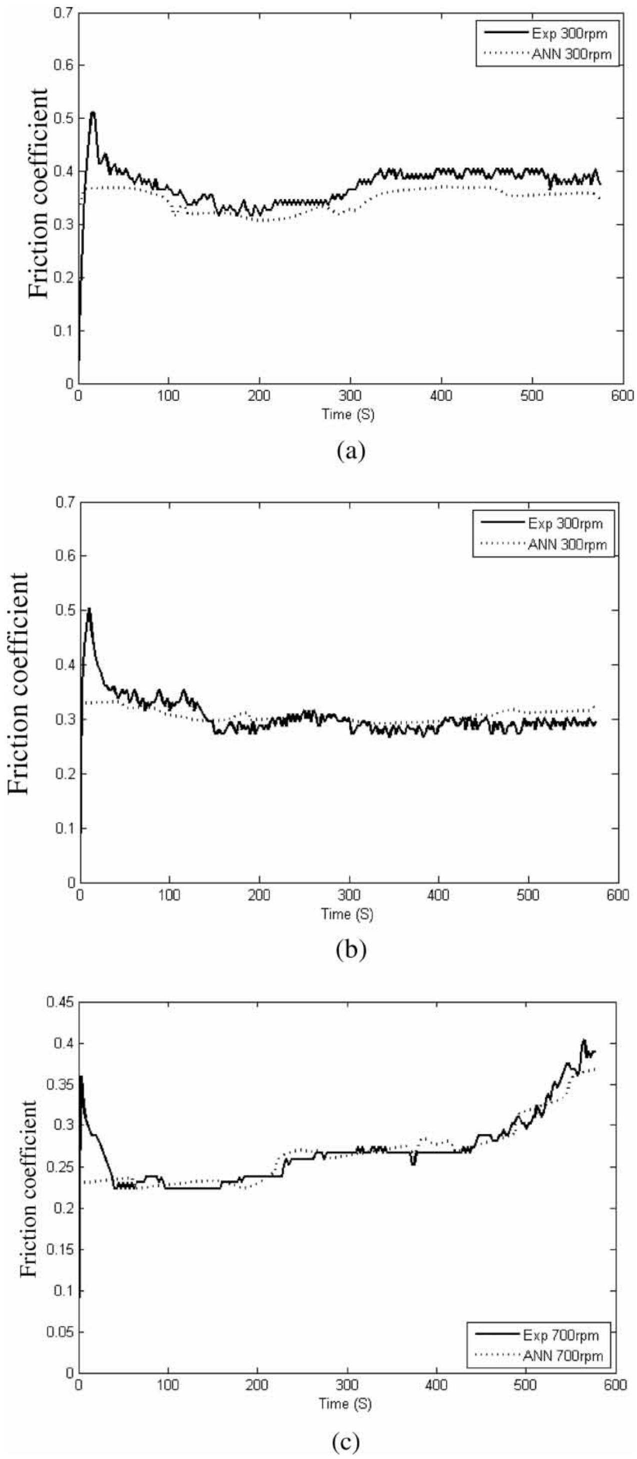

Fig. 14 Experimental and ANN friction coefficient results at different parameters of CGRP composites in AP-O: (a) AP-O at 70N applied force at 300 r/min; (b) AP-O at 100N applied force at 300 r/min; and (c) AP-O at 100N applied force at 700 r/min

date very complex, which led to this difference of the prediction and the experimental ones in N-O. In spite of this, it can say that the usage of ANN for such application is acceptable. The maximum error, between the ANN and the experiment of the N-O, is reached at about 6 per cent only (Fig. 13c). The following sections show the predicted results at different parameters.

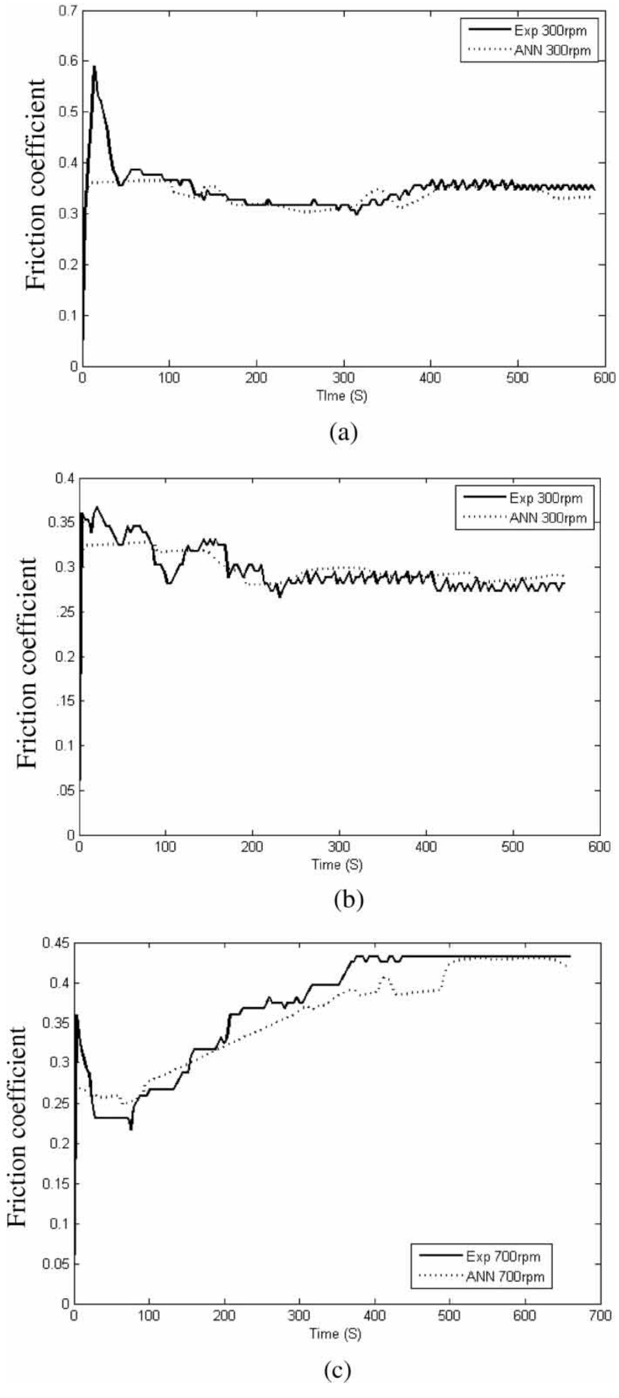

Fig. 15 Experimental and ANN friction coefficient results at different parameters of CGRP composites in P-O: (a) P-O at 70N applied force at 300 r/min; (b) P-O at 100N applied force at 300 r/min; and (c) P-O at 100N applied force at 700 r/min

4.2 Prediction of friction coefficient

The experimental results were conducted at different loads (30–100 N) and speeds (300–700 r/min). Figures 16 and 17 show the friction coefficient at different parameters and different orientations. The developed ANN model was then used to predict the friction coefficient values, beyond the trained domain. In Fig. 16, it can be seen that the experimental and predicted friction coefficient values follow the same trend. This indicates the ability of ANN to predict the friction coefficient at unknown parameters. Similarly, Fig. 17 shows the friction coefficient at different sliding speeds, i.e. the friction coefficient values are following the trends as the experimental values, especially for speeds close to the training points. To show the possibility of using ANN for multi-layered composite at different orientations, Fig. 18 shows the SD of the ANN results for three different orientations of the composite. The figure indicates that there is a variation in the prediction of the friction coefficient of the composite in three orientations. In other words, it indicates that the P-O exhibits less error, followed by AP-O and then N-O. As mentioned earlier, in N-O, modifications occurred on the composite surface during the sliding test, and could be the reason for higher SD.

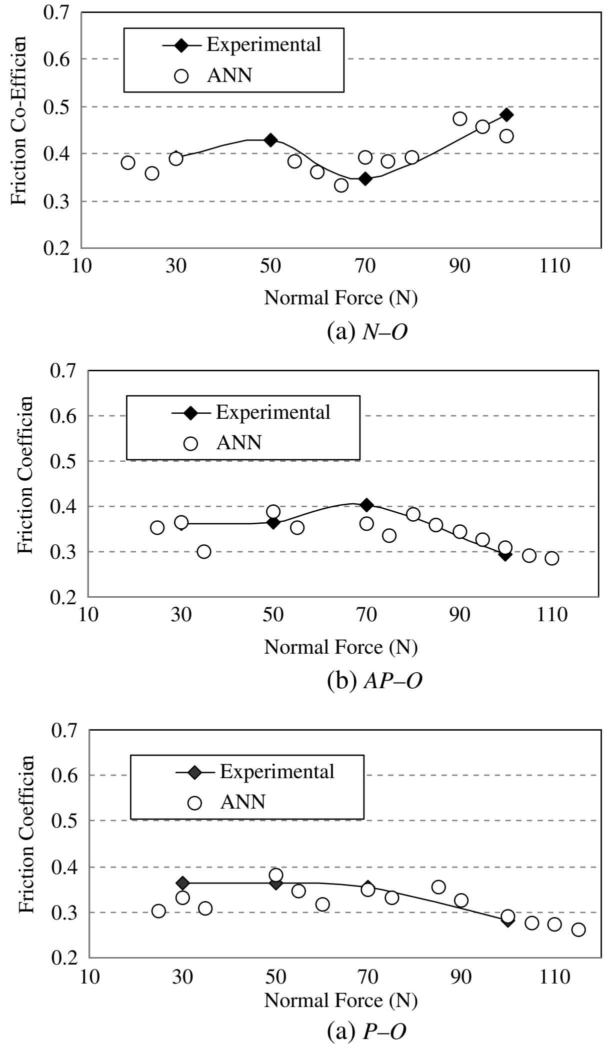

Fig. 16 ANN and experimental prediction comparison in three different orientations at various forces

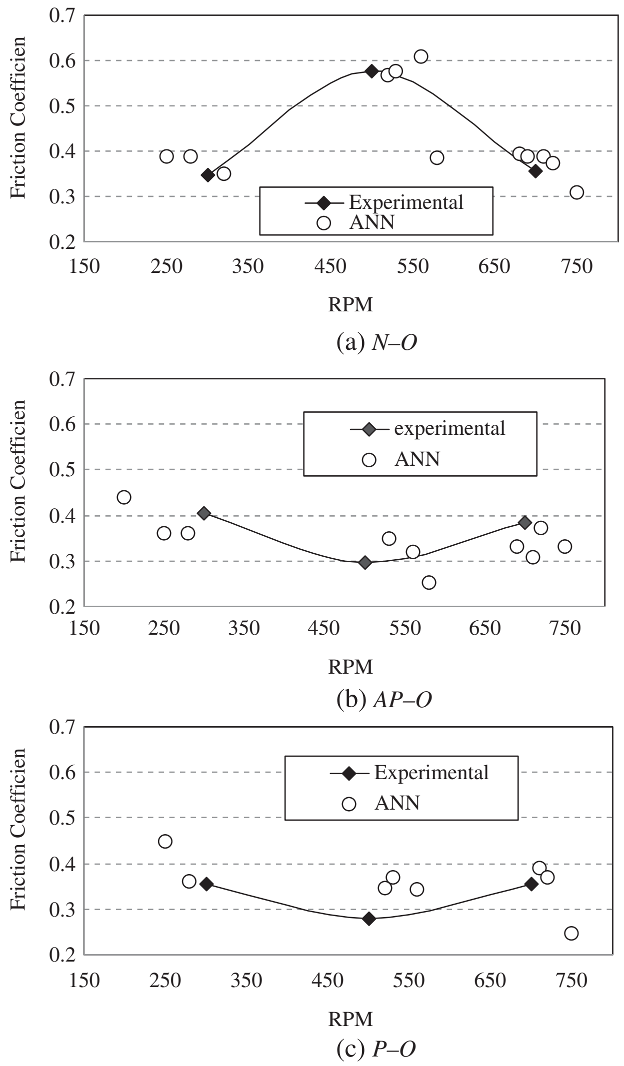

Fig. 17 ANN and experimental prediction comparison in three different orientations at various RPM

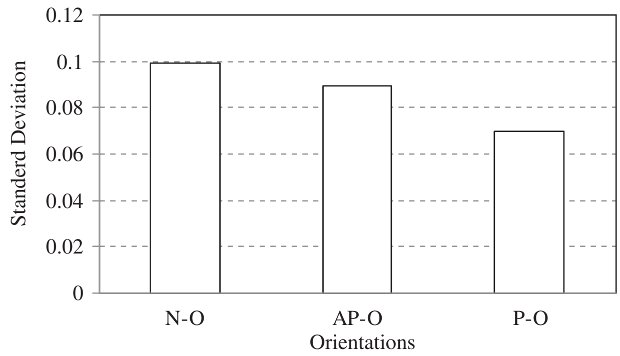

Fig. 18 Standard deviation comparison of different orientations

In the present topic, the CGRP friction coefficient was predicted with satisfactory results using the ANN technology. Previously, similar work has been carried out to predict the tribological properties of other composite materials using the ANN. A comparion of the previous works and the current work is shown in Table 2.

From the above comparison, it can be seen that the current work's performace is lower than the previous works. However, it is also noticeable that the current work has a immensely large input data volume (7389 sets) compared to other works (25–80 sets). Moreover, the input data for the present work has very large deviations and fluctuations in the experimental results, especially in different orientations of the fibre composition. This could be the reason for a relatively weaker performance in the present work. However, the prediction ability of ANN in the steady-state phase is about 90 per cent. As the running-in period experiences high amount of fluctuation, the overall prediction performance is low in that region.

The configuration of neurons is a very important aspect of ANN which affects the performance. The above comparison shows the variety of neural configurations on different applications. The complexity or the simplicity of the neural configuration is dictated by the type of training data. For example, when trained with only one orientation dataset (e.g. antiparallel), a multi-layered ANN model 4-[10-5]-1 performed better than a single-layered model. In fact, during the ANN model development, some complex multi-layered ANN models especially 4-[20-10]-1 and 4-[25-15-5]-1 provided good results. The comparison above indicates that neural configuration is a case to case basis.

Table 2 ANN performance of current and previous models

Work	Material	Transfer function	Training function	Layer configuration	Trainning sata volume (sets)	Performance
Current	CGRP	Tan-sigmoid	TrainLM[a]	4-[40]-1	7389	0.901 689
[**4**]	SFRT(short fibre reinforced thermoplastic)	unknown	TrainBR and TrainCGB[a]	9-[15-10-5]-1	80	0.999 82
[**5**]	PA4.6 polymide composite	Tan-sigmoid	TrainCGB and TrainGDX[a]	9-[15-10-5]-1	70	0.9–1.0
[**16**]	PEEK CF30 composite	unknown	TrainBR and TrainLM[a]	2-[7]-1	25	0.9

[a]TrainBR: Bayesian Regularization Training Algorithm, TrainCGB: Powell–Beale conjugate gradient Training Algorithm, TrainGDX: Gradient descent with momentum and adaptive learning rule Training Algorithm, and TrainLM: Levenberg–Marquardt Training Algorithm.

5 CONCLUSION

The current work on ANN was an attempt to explore the possibility of using ANN technology to predict the friction coefficient of multi-layered CGRP composite material. Fibre orientation, applied load, rotational speed, and the sliding duration are the influences for the friction coefficient. The developed model showed promising results for the prediction of friction cofficient, especially in the steady-state region. Single-layer ANN models with a large number of neurons provided improved results. The training function also showed a significant effect on the ANN performance. The TrainLM function exhibited the best performance for the current work.

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