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Modeling of sliding wear characteristics of Polytetrafluoroethylene (PTFE) composite reinforced with carbon fiber against SS304

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ABSTRACT

Introduction. Over the last decade, composite materials based on polytetrafluoroethylene (*PTFE*) have been increasingly used as alternative materials for automotive applications. *PTFE* is characterized by a low coefficient of friction, hardness and corrosion resistance. However, this material has a high wear rate. A group of researchers attempted to improve the wear resistance of *PTFE* material by reinforcing it with different fillers. **The purpose of the work:** This study experimentally investigates the dry sliding wear characteristics of a *PTFE* composite reinforced with carbon fiber (35 wt.%) compared to SS304 stainless steel. In addition, experimental mathematical and ANN models are developed to predict the specific wear rate, taking into account the influence of pressure, sliding speed, and interface temperature. **The methods of investigation.** Dry sliding experiments were performed on a pin-on-disk wear testing machine with varying the normal load on the pin, disk rotation, and interface temperature. Experiments were planned systematically to investigate the effect of input parameters on specific wear rates with a wide range of design space. In total, fifteen experiments were carried out at a 5-kilometer distance without repeating the central run experiment. Sliding velocities were obtained by selecting the track diameter on the disk and corresponding rotation of the disk. A feedforward back-propagation machine learning algorithm was used to the *ANN* model. **Results and Discussion.** This study finds better prediction accuracy with the *ANN* architecture having two hidden layers with 150 neurons on each layer. This study finds an increase in specific wear rates with normal load, sliding velocity, and interface temperature. However, the increase is more prominent at higher process parameters. The normal load followed by sliding velocity most significantly affects the specific wear rate. The results predicted by the developed models for specific wear rates are in good agreement with the experimental values with an average error close to 10%. This shows that the model could be reliably used to obtain the wear rate of *PTFE* composite reinforced with carbon fiber (35 wt.%) compared to *SS304* stainless steel. This study finds scope for further studies considering the effect of varying *ANN* architectures, different amount of neurons, and hidden layers on the prediction accuracy of the wear rate.

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Introduction

Tribological behavior of sliding contact surfaces have prominent effect on power loss, heat generation, and the overall performance of the system. Researchers have made several attempts to replace conventional material with a composite one that is lighter and more economical, suitable for a particular application. Over the last decade, composite materials based on polytetrafluoroethylene (*PTFE*) have been increasingly used as alternative materials for automotive applications.

PTFE commercially known as *Teflon* is mostly preferred as an alternative material when having sliding contact. *PTFE* is characterized by a low coefficient of friction, hardness, and corrosion resistance. However,

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this material has a high wear rate. A group of researchers attempted to improve the wear resistance of *PTFE* material by reinforcing it with different fillers, considering its wide range of automotive applications having sliding contact [1-5].

Sonawane et al. [1] observed better sliding wear properties for 35% carbon fiber filled *PTFE* material against 25% carbon filled *PTFE* when using *Al6061* as countersurface. *AISI 304* is the most used austenitic stainless steel in household, automotive and industrial applications. With a view to consider *PTFE* composite as an alternative material for automotive applications, *Chinchanikar et al.* [2] performed dry sliding wear characteristics of *PTFE* composite reinforced with carbon fiber (35 wt.%) against *AISI 304* stainless steel. Their study observed development of transfer film with increase in pressure at sliding interfaces that assisted in decreasing specific wear rate. However, further studies are required on the development of transfer film on the sliding surface considering the effect of normal load, sliding velocity, and temperature.

Unal et.al. [3] investigated the wear of *PTFE*, *PTFE*+17% glass fiber, *PTFE*+25% bronze, *PTFE*+35% carbon fiber. Their study found a decrease in friction coefficient for the *PTFE* and composites up to a certain normal load beyond which friction and wear rate increased. Their investigation observed the formation of thin and uniform transfer film in the case of *PTFE* and disruption of transfer film in the case of bronze- and carbon-filled composite.

Sachin [4] studied the wear behavior of *PTFE* and its composites including glass and carbon as filler. Their study observed an increase in volume loss with the increase in load and distance. However, volume loss decreased with the increase in grit size and was considered to be a dominant factor for the wear resistance of the materials. Their study showed that carbon-filled composites had greater wear resistance than fiberglass-reinforced *PTFE* matrix.

Venkateswarlu et al. [5] investigated mechanical properties such as hardness, tensile strength, and elongation of pure *PTFE* and different *PTFE*-composites with varying filler concentrations. Their study observed an increase in hardness with the optimum filler content and beyond this value hardness was decreased. On the other hand, tensile strength and elongation of *PTFE*-composites decreased with the increase in filler content. Their study found bronze as a promising filler material for obtaining higher tensile strength and lower elongation.

Wang et al. [6] experimental study revealed that single incorporation of short carbon fiber and graphite significantly reduces friction in the case of composites based on *PI* and its wear resistance. *Song et al.* [7] investigated the effect of addition of glass fiber and molybdenum disulphide (MoS_2) on wear and friction of *PTFE*-composite with chopped carbon fiber (20 wt.%) as filler. Their study found an increase in friction coefficient with the sliding speed and its decrease with the load when used steel ring as counter surface. The addition of MoS_2 to *PTFE* composite increased its scratch resistance and therefore reduced the wear rate.

Gujrathi et al. [8] experimental studies also observed reduction in the wear rate due to filler materials addition. Their study observed that the development of a protective layer between the pin and counterface assisted in decreasing the wear volume loss. *Shen et al.* [9] investigated the tribological performance of *PTFE* filled SiO_2 particles-epoxy composites. Their study observed that adding 10-15% of *PTFE* yields in lowest coefficient of friction and wear rate under dry sliding with bearing steel balls as counterface. In another study, *Shen et al.* [10] compared the abrasion resistance of *PTFE* using Al_2O_3 particles with sizes in the range 5 to 200 μm. Their study revealed that the abrasive size significantly influences the tribological characteristics of tribo-pairs.

Sawyer et al. [11] observed the wear resistance of PTFE composite reinforced with 40 nm alumina particles increased with filler concentration. Kim et al. [12] study found a decrease in friction coefficients with the normal load and sliding velocity. Wear rates observed as decreasing with the rise in normal load. However, initially wear rate increased with the sliding velocity and then decreased.

Wang et al. [13] investigated the wear properties of textured stainless steel opposed to polymer surfaces. *EDX* analysis performed by them showed different wear behavior. *Desale* and *Pawar* [14] studied the wear and friction characteristics of solid lubricant *PTFE* reinforced with carbon, MoS_2, glass fiber, polyether ether ketone particles under dry and wet conditions against SS304 stainless steel. They observed the minimum wear rate for the *PTFE* composite filled with 15% glass fiber and 5% MoS_2 particles.

Artificial neural network (*ANN*) model has been considered as potential and good tool for mathematical modelling of complex and nonlinear wear behavior [15]. The *ANN* approach, inspired by the biological nervous system, simulates many complicated real-life nonlinear and complex relationships. *Ibrahim et al.* [15] developed an *ANN* model to determine wear of *PTFE* composites. Further, the performance of the models was compared with conventional multilinear regression model (*MLR*). Their study showed that the ANN model has higher predictive accuracy. Sensitive analysis showed that the volume fraction of the reinforcing filler, the sliding distance and the density of the composites tend to be significant parameters.

ANN helps to ensure the accuracy in modelling nonlinear relations of composite material properties. And further helps to evaluate the influence of many input parameters on material's performance. A group of researchers found that *ANNs* are highly accurate in modelling the mechanical behavior of composite materials [16]. Researchers have put a lot of effort into modeling sliding wear characteristics using ANNs. A group of researchers observed that the performance of an *ANN* model depends on the quantity and type of data provided while training. Further, it is reported that it is necessary to determine the significant set of parameters to save time and train an *ANN* model effectively [17]. The *ANN* modelling assists in understanding the process physics that would improve the process performance by facilitating better process control.

Although sufficient work has been carried out by the researchers to evaluate the performance of reinforced composites, very few have modeled sliding wear characteristics of *PTFE* composite reinforced with carbon fiber against *SS304* stainless steel. With this view, this study develops experimental-based mathematical and *ANN* models to predict the sliding wear characteristics of *PTFE* composite reinforced with carbon fiber against *SS304* stainless steel taking into account the impact of normal load, interface temperature, and sliding velocity.

Experimental Details

Carbon-filled PTFE has excellent frictional properties, mechanical and wear properties. During manufacturing, carbon may be added in the form of powder or fibre. A hot compression moulding process is used to prepare a *PTFE* pin reinforced with carbon fibre (35 wt.%). The reinforced *PTFE* composite specimens had diameter and length of 10 mm and 40 mm, respectively.

Cylindrical pins were further machined to have an individual length of 31 mm considering the position of the pin heater holder in which the test specimens (pin) get fitted. Three sets of *SS304* stainless steel plates were used as the material for discs having an outer diameter of 165 mm and a thickness of 8 mm. All plates were hardened to 60 HRC and machined to get an almost equal surface roughness of 1.6 μm.

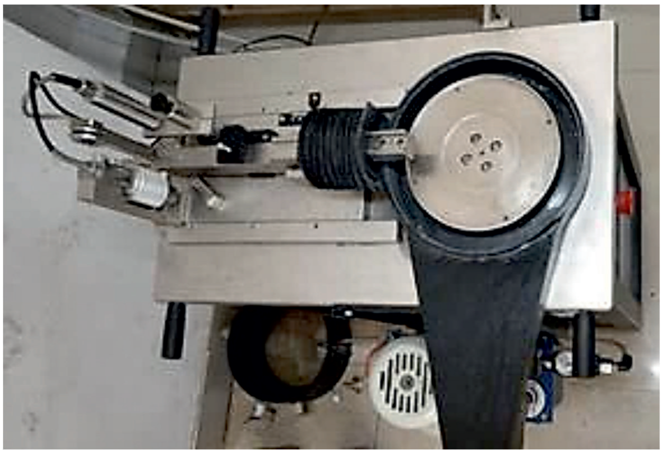

Fig. 1. A pin-on-disk machine showing disk arrangement

A pin-on-disk machine was used to perform dry sliding experiments (Fig. 1). This machine has a facility to vary the speed in the range from 200–2000 rpm and normal load in the range of 20-200 N. The machine is equipped with a heater for obtaining the effect of interface temperature on wear characteristics of sliding surfaces. A thermocouple is used to obtain information about the temperature of the pin. This machine also has a facility to carry out wear tests taking into account the impact of lubrication.

Cylindrical pins used as test specimens varied in size and had a diameter of 3, 6, 8 and 10 mm. Each pin size required a different holder type. This holder was mounted on a rod that has a seesaw arrangement. The weights attached at the other end of the rod was transferred to cylindrical pin and hence, plate (disk) through steel wire. Friction force and the linear wear (in μm) were measured by sensors that the machine was equipped with. Proximity sensor that the machine is equipped with helped in measuring the speed of the disk (rpm) having least count of 1 rpm with 1 % accuracy.

In general, in the compression process pressure on the piston ring varied in the range 2 to 25 bar and temperature in the range 50–200°C with a sliding velocity of 5 m/s. Based on this, ranges of normal load, interface temperature and sliding speed were selected, which are shown in Table 1. Experiments were planned systematically to investigate the effect of input parameters on specific wear rates with a wide range of design space. In total, fifteen experiments were carried out at a 5-kilometer distance without repeating the central run experiment. Sliding velocities were obtained by selecting the track diameter on the disk and corresponding rotation of the disk.

Table 1

Levels of parameters selected to evaluate specific wear rate

Parameter	Low level	Moderate level	High level
Normal load (*FN*) (N)	20	100	180
Interface temperature (*T*) (°C)	50	100	150
Sliding velocity (*v*) (m/s)	2	5	8
Track distance: 5 km			

Results and Discussion

Dry sliding wear characteristics of *PTFE* composite (a pin material) against *SS304* stainless steel plate (a disk material) were performed on a pin-on-disk machine. Experiments were performed as per *DoE*; normal load, interface temperature, and sliding velocity were varied in the ranges as shown in Table 1.

On the pin-on-disk machine, the normal load was applied to the pin by transferring (seesaw arrangement) the weights attached at the other end of the rod. The corresponding temperature was set by turning on the heater and the temperature attained was measured by a thermocouple. The required sliding speed was obtained by selecting the appropriate track diameter on the disk and selecting the corresponding rotation speed of the disk. The test was carried out at a 5-kilometer track distance (approx. 14–17 min). A digital readout for wear, friction force corresponding to process parameters such as normal load, temperature, and disk rotation speed was monitored from the Control panel. The Control panel was attached to a desktop computer. Variation in friction force and wear with respect to test time to cover track distance of 5 km was also monitored on a desktop computer using *Windcom* software.

Experimental matrix with process parameters such as normal load, interface temperature, sliding speed and corresponding results is shown in Table 2. Theoretically, the wear rate was calculated by Eq. 1. However, volume loss was obtained by measuring the weight loss of the pin prior to and following the test. Volume loss is calculated by using Eq. 2.

$$\text{Specific wear rate} = \frac{\text{volume loss}}{\text{load} \times \text{sliding distance}}, \tag{1}$$

where

$$\text{Volume loss} = \frac{\text{mass loss}}{\text{density}}. \tag{2}$$

An experimental-based mathematical model as shown in Eq. 3 was developed to predict wear rate in terms of normal load (*FN*), interface temperature (*T*), and sliding speed (*v*). The developed model is also

Table 2

Experimental matrix and results

Expt. No.	FN (N)	T (°C)	v (m/s)	Weight (gm)		Weight loss (gm)	Volume loss (mm^3)	Specific wear rate (× 10^{-5}) (mm^3/Nm)
				Before test	After test			
1	50	70	7	5.191	5.185	0.006	2.65	1.06
2	100	100	5	5.223	5.207	0.016	7.75	1.55
3	50	130	7	5.251	5.244	0.007	3.15	1.26
4	150	130	3	5.196	5.168	0.028	13.275	1.77
5	100	50	5	5.134	5.122	0.012	5.9	1.18
6	180	100	5	5.061	5.017	0.044	20.97	2.33
7	150	130	7	5.172	5.130	0.042	19.875	2.65
8	100	100	2	5.211	5.200	0.011	5.2	1.04
9	20	100	5	5.183	5.181	0.002	0.77	0.77
10	150	70	7	5.214	5.181	0.033	15.675	2.09
11	100	100	8	5.252	5.232	0.020	9.4	1.88
12	150	70	3	5.211	5.185	0.026	12.525	1.67
13	100	150	5	5.133	5.114	0.019	9.05	1.81
14	50	130	3	5.183	5.178	0.005	2.35	0.94
15	50	70	3	5.221	5.217	0.004	1.725	0.69

useful to understand the parametric impact on wear. In the equation k, a, b, and c are constants that are obtained by developing polynomial regression model based on the experimental data.

$$\text{Specific wear rate } (W_s) = k\, F_N{}^a\, T^b\, v^c. \tag{3}$$

A *DataFit* software was used to obtain the correlation between wear, normal load, temperature, and sliding velocity as expressed in Eq. 4. The correlation coefficient obtained (R^2 value) is 0.9791 showed that the developed empirical expression could be effectively used to know wear rate of a *PTFE* composite reinforced with carbon fiber (35 wt.%) against *SS304* stainless steel in the range of parameters selected in this study.

$$\text{Specific wear rate } (W_s) = 9.89 \times 10^{-8}\, F_N{}^{0.6307} T^{0.333} v^{0.403}. \tag{4}$$

From the exponents of normal load, interface temperature, and speed, it can be seen that specific wear rate is significantly affected by normal load and after that by sliding speed, and temperature. To have a clear understanding of the effect of input parameters on specific wear rate 3-D graphs are plotted for specific wear rate using empirical Eq. (4), varying with normal load, interface temperature, and sliding speed. 3-D surface curves are plotted by varying the two process parameters at a time, keeping the other parameter constant at the mid-value of the ranges of the parameters as depicted in Table 1.

The 3-D plots reflecting the variation in the specific wear rate are shown in Figs. 2, *a*–*c*. Fig. 2, *a* depicts the variation in the wear rate with the normal load and interface temperature considering the sliding velocity of 5 m/s. Fig. 2, *b* shows the variation in wear rate with the sliding speed and normal load, and Fig. 12, *c* depicts variation with the interface temperature and sliding speed. The plots are based on varying two process parameters while maintaining a constant value of the third parameter (FN = 100N, T = 100°C, and v = 5 m/s). This study found an interaction effect of the process parameters on the *PTFE* composite wear rate against *SS304* stainless steel.

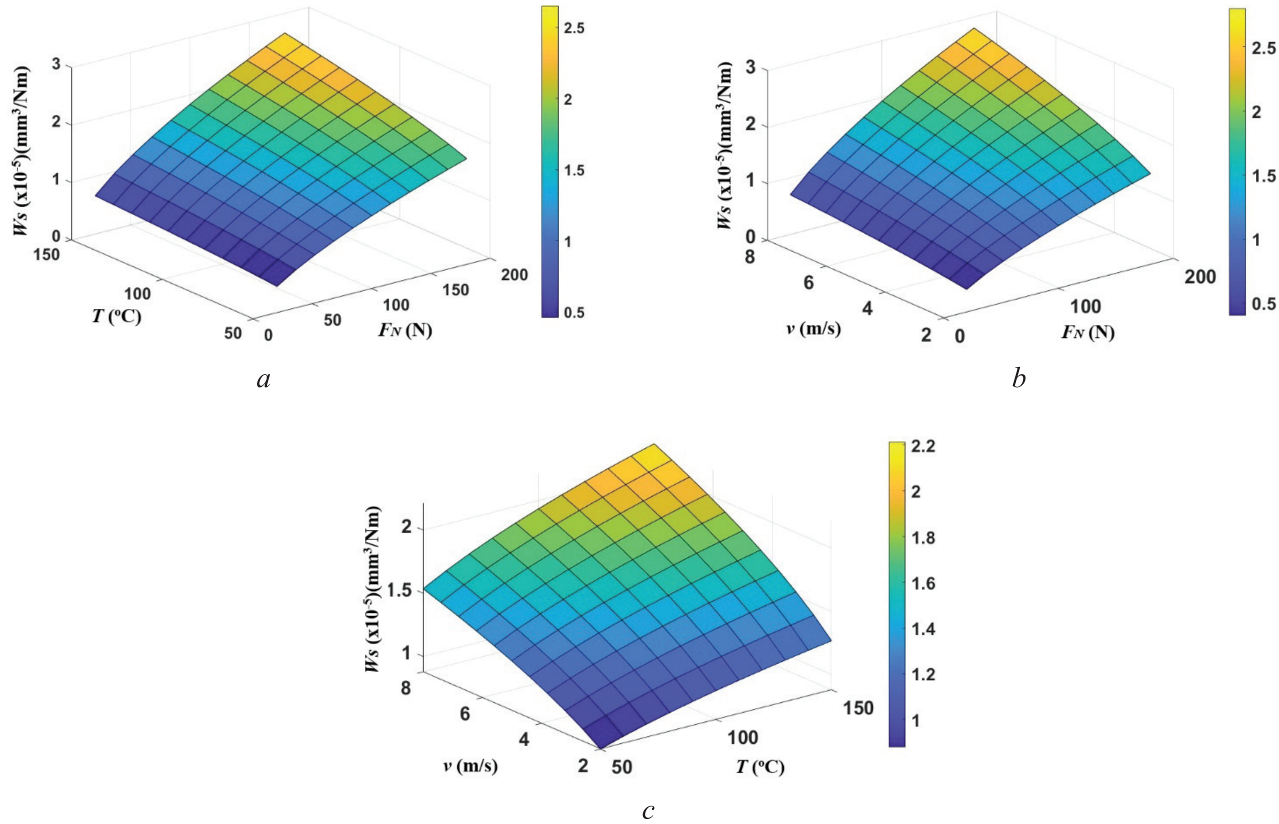

Fig. 2. 3-D plots showing specific wear rate varying with:
a – Normal load and interface temperature; *b* – Normal load and sliding speed; *c* – Interface temperature and sliding speed

It is apparent that the specific wear rate increases with the normal load, interface temperature, and sliding velocity. However, the increase in specific wear rate will become more noticeable at higher process parameters. The normal load followed by sliding velocity and interface temperature can be seen as most significant parameters affecting the wear rate. This can be also confirmed by the higher exponent value for the normal load followed by for sliding speed and then for interface temperature in Eq. (4). This study finds that wear is prominently affected by the normal load, especially at higher values of interface temperature and sliding speed.

Artificial neural network (*ANN*) is a computational technique that can model relationships between input parameters and output responses. A typical *MLP* architecture which is most commonly used is shown in Fig. 3. *MLP* is characterized by three different layers namely input layer, hidden layer, and output layer, which consist of an interconnected group of artificial neurons. The number of neurons present in the input layer and output layer is equal to the number of input variables and corresponding output values.

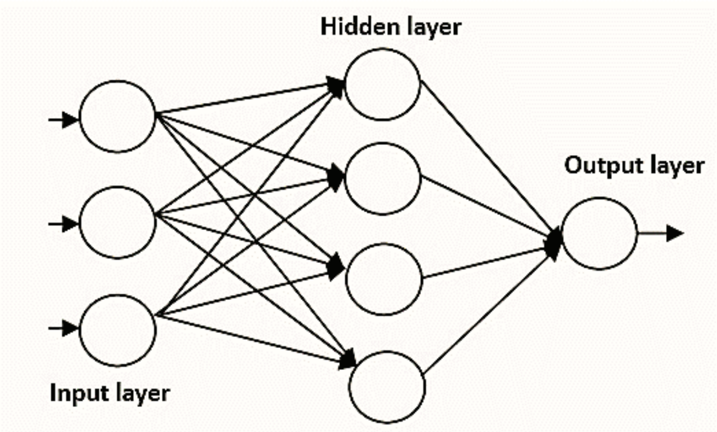

Fig. 3. Typical *ANN* architecture

To predict output with higher accuracy, training of the developed network is essential. In the training process of a model, the synaptic weights of the network are modified in an orderly fashion to attain the desired output. Most used training algorithms is the error backpropagation algorithm. For a typical *ANN* algorithm, at the first step the weights and thresholds are initialized. Then, the output of each neuron is calculated from the input data and initialized weights which lead to the final output prediction of the network. Then, the error at output node is calculated and based on an error the weights are modified. And weights in the previous layers are modified by back-propagating errors calculated at output layer nodes [18]. This process is repeated for a set of input and output of training data. The training stops when the ANN output is sufficiently close to the expected output for each set.

ANN model is built to obtain the wear considering the input parameters as the normal load, interface temperature, and sliding speed using *MATLAB Toolbox*. The *ANN* architecture has three layers namely input, output, and hidden layers (Fig. 4). The input layer has 3 neurons, the output layer has 1 neuron, and there is appropriate number of neurons on the hidden layer. The neurons are selected by checking the network accuracy. The number of neurons on the hidden layer can be changed if the network does not perform well after training.

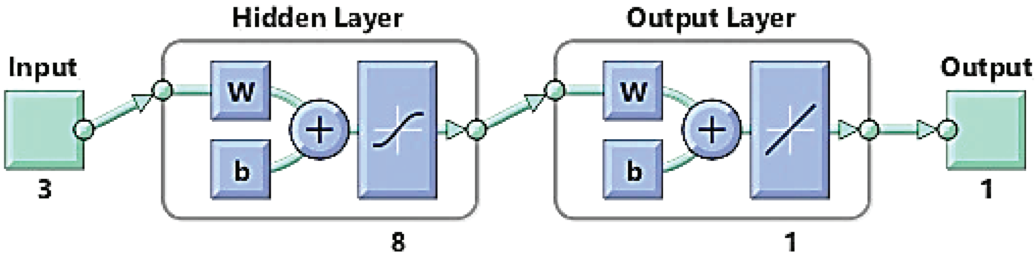

Fig. 4. ANN architecture to obtain wear rate

A feed-forward neural network maps a data set of numeric inputs with a set of numeric targets. The *Neural Fitting app* of *MATLAB Toolbox* helps to select data and create and train a network and evaluate its performance using mean square error and regression analysis. A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons is selected that fits multi-dimensional problems arbitrarily well, given consistent data and enough neurons in its hidden layer. The network has been trained with the *Levenberg-Marquardt* backpropagation algorithm.

In a neural network, three kinds of samples are used for the training and validation of test data. In the present work, around 70 % of the data is used for training the neural network. The network is adjusted according to its error. Around 15 % of the data is used for validation of the results predicted by the trained neural network. These validation data sets are used to measure network generalization, and to halt training when generalization stops improving. And around 15 % data is used for testing the results predicted by the neural network. These data sets do not affect training and so provide an independent estimation of network performance during and after training.

The next important step is to determine network architecture to obtain better accuracy of the predicted results. In this study, a better-predicted accuracy of 0.9747 has been observed with eight neurons in the hidden layer. Further, the network is to be trained using either the *Levenberg-Marquardt* algorithm or *Bayesian* Regularization, or *Scaled Conjugate Gradient* algorithm. However, the researchers have mostly used the *Levenberg-Marquardt* algorithm. This algorithm is comparatively faster than other algorithms. However, this algorithm requires more memory.

Neural network training performance is measured in terms of mean squared error (the average squared error between targets and outputs). Lower values are better. Regression (R) values measure the correlation between outputs (predicted values) and targets (inputs). Neural network regression graphs with regression coefficients obtained while training the model, during validation, testing, and for the entire data set are shown in Figs. 5, *a–d* respectively.

The values of regression coefficients close to one for training, validation, testing, and for the entire data set shows that the developed neural network model could be reliably used for predicting *PTFE* composite wear rate reinforced with carbon fibre (35 wt.%) against *SS304* stainless steel within the domain of the parameters selected in this study.

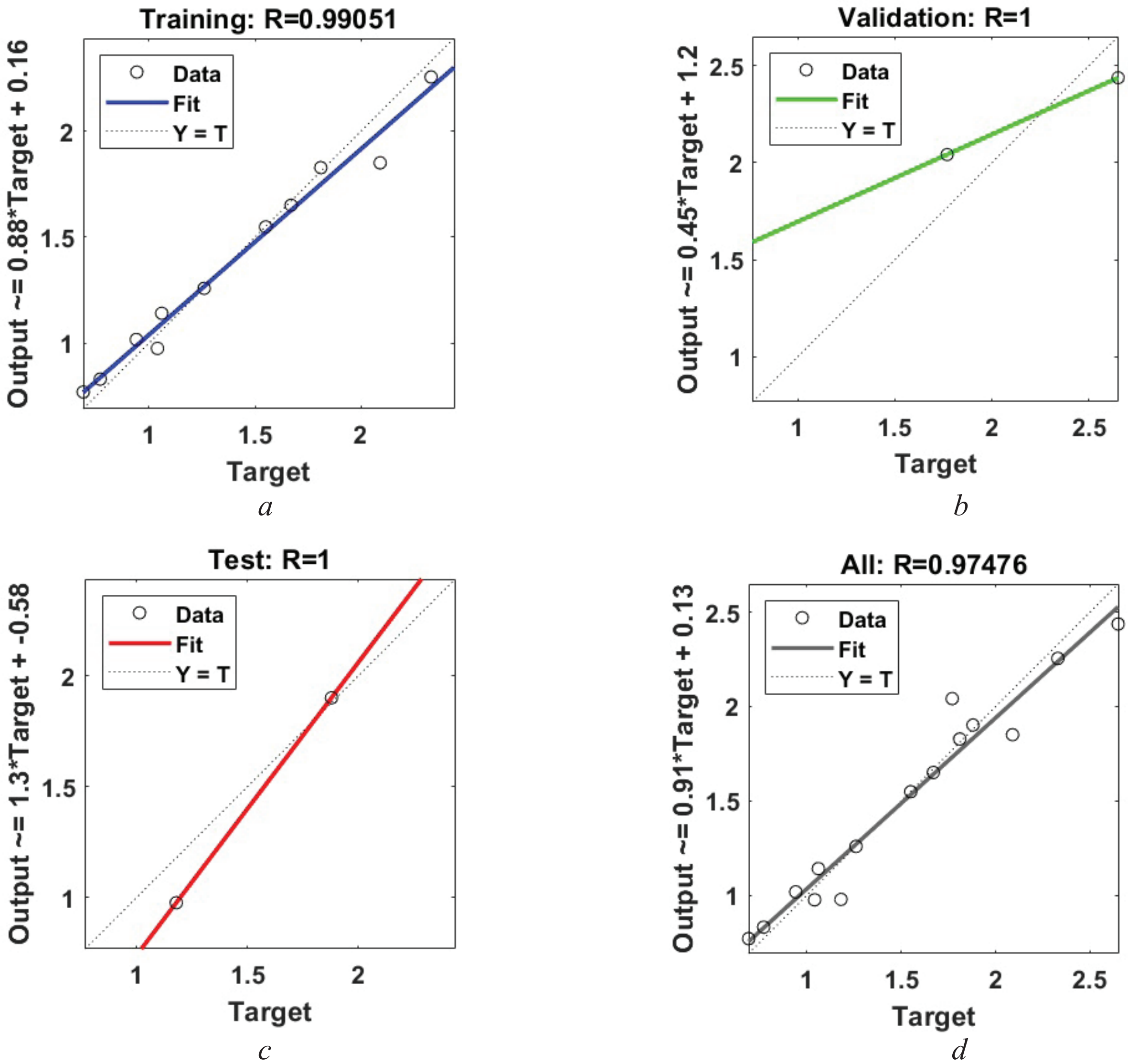

Fig. 5. Neural network (*a*) Training; (*b*) Validation; (*c*) Test; (*d*) All data set

Further, the validation experiments were performed using the process parameters different than that are used for developing the models. A comparative of the predicted results with the experimental-based mathematical model and artificial neural network (*ANN*) is shown in Table 3. The model accuracy is assessed by obtaining % error between the predicted and experimental values of wear rate for different process parameters. The % error is obtained using Eq. (5).

$$\text{Average error} = \frac{(\text{Predicted value} - \text{Expt value}) \times 100}{\text{Expt value}}. \quad (5)$$

Table 3 presents data on the specific wear rate predicted by the developed models. Predicted results are seen in good agreement with the experimental values with average error of 10.16 % for experimental-based model and 3.57 % for *ANN* model. It is apparent that the results predicted by the *ANN* model are having a better agreement with the experimental results as compared to experimental-based model.

Conclusions

This study attempted modelling sliding wear characteristics of PTFE composite reinforced with carbon fiber (35 % by weight) against SS304 stainless steel. Experiments were carried out on the pin-on-disk at different normal loads, interface temperature, and sliding velocities. An experimental-based mathematical

Table 3

Validation experiments and modeling results

Expt. no.	F_N (N)	T (°C)	v (m/s)	Specific wear rate (x 10^{-5}) (Ws) (mm^3/Nm)			|% Error|	
				Expt. value	Statistical model	*ANN* model	Statistical model	*ANN* model
1	130	1.72	1.72	1.72	1.72	1.72	5.06	1.72
2	90	4.97	4.97	4.97	4.97	4.97	19.16	4.97
3	40	5.04	5.04	5.04	5.04	5.04	15.33	5.04
4	140	1.29	1.29	1.29	1.29	1.29	7.72	1.29
5	170	3.24	3.24	3.24	3.24	3.24	7.61	3.24
6	70	5.13	5.13	5.13	5.13	5.13	6.10	5.13
Average error							10.16	3.57

model and ANN model were developed to predict specific wear rates to understand the parametric effect on specific wear rate. The followings conclusions could be drawn from the present study:

• It has been observed that the wear rate increased with the normal load, interface temperature, and sliding velocity. However, the increase was more prominent at higher process parameters. The normal load followed by sliding velocity and interface temperature were found as most significant parameters affecting the wear rate. This was also confirmed by the higher exponent value for the normal load followed by for sliding speed and then for interface temperature.

• The correlation coefficient of 0.97 observed for both the developed experimental-based mathematical and *ANN* models shows that the model could be reliably used to obtain wear rate of *PTFE* composite reinforced with carbon fiber (35% by weight) against *SS304* stainless steel.

• The results predicted by the developed models for specific wear rate were in good agreement with the experimental values with an average error close to 10%. However, the results predicted by the *ANN* model showed better agreement (avg. error of 3.57 %) with the experimental results than statistical-based models (avg. error of 10.16 %).

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Conflicts of Interest

The author declare no conflict of interest.