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Chapter

Specific Wear Rate Modeling of Polytetraflouroethylene Composites Via Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) Tools

Musa Alhaji Ibrahim, Yusuf Şahin, Auwal Ibrahim, Auwalu Yusuf Gidado and Mukhtar Nuhu Yahya

Abstract

Lately, artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) models have been recognized as potential and good tools for mathematical modeling of complex and nonlinear behavior of specific wear rate (SWR) of composite materials. In this study, modeling and prediction of specific wear rate of polytetraflouroethylene (PTFE) composites using FFNN and ANFIS models were examined. The performances of the models were compared with conventional multilinear regression (MLR) model. To establish the proper choice of input variables, a sensitivity analysis was performed to determine the most influential parameter on the SWR. The modeling and prediction performance results showed that FFNN and ANFIS models outperformed that of the MLR model by 45.36% and 45.80%, respectively. The sensitivity analysis findings revealed that the volume fraction of reinforcement and density of the composites and sliding distance were the most and more influential parameters, respectively. The goodness of fit of the ANN and ANFIS models was further checked using t-test at 5% level of significance and the results proved that ANN and ANFIS models are powerful and efficient tools in dealing with complex and nonlinear behavior of SWR of the PTFE composites.

Keywords: artificial neural network, adaptive neuro fuzzy inference system, multi linear regression, specific wear rate, PTFE reinforced composites

1. Introduction

In the study of tribology, highly nonlinear and very complex relationship exists. Specific wear rate of materials especially polymer matrix composites emanates from scores of intricate associations on both microscopic and macroscopic levels between surfaces which are in contact [1]. These associations depend upon tribological, geometrical as well as material behaviors of the contacting surfaces and the sliding conditions for example, temperature, type of contact, lubricating conditions, applied load, etc. [2]. Simulation of tribological properties usually deals with building of mathematical models extracted from practical data. The numbers of these models were obtained to simulate specific wear rate of materials under restricted conditions. Yet, no distinctive model was universalized to reveal the specific wear rate of polymer matrix composites.

Of recent soft computing techniques such as artificial neural networks (ANNs) and adaptive neuro fuzzy inference system (ANFIS) have emerged as potential and effective tools to model wear property of poly-based composites, owing to their abilities to learn from experimental data and generalize [3]. The pioneering studies of exploring the potentials of these soft computing methods especially ANN in the prediction of wear properties were carried out by Hutching et al. and Jones, Jensen and Fusaro [4–5], respectively. Thereafter, many researchers applied the methods to analyze and predict the wear property polymer matrix composites under different test conditions and material compositions. In the physical experimentation of wear simulation, known material compositions and properties, experimental parameters are fed into the ANN and ANFIS models as inputs and the anticipated specific wear rate responses of the virtual scenario are computed. The fundamental advantage of ANN and ANFIS modeling in comparison to other modeling techniques are in their capabilities to provide accurate approximations or predictions when complexity and nonlinearity are involved at the same time. Complexity and nonlinearity cannot be handled by traditional curve fits [1]. More so, ANN and ANFIS models can effectively deal with these.

Velten, Reinicke and Friedrich [6] explored the potential of ANN when they predicted wear volume of short fiber reinforced polymeric composites. They found that with increase in the number of inputs the prediction quality of the ANN model was improved. Zhang, Friedrich and Velten [7] used multilayered feed forward neural network to predict the coefficient of friction and specific wear rate of short fiber reinforced polyamide. The results indicated a good agreement with experimental results. Jiang, Zhang and Friedrich [8] applied ANN model to predict both the wear and mechanical properties of polymer matrix composites. They established a 3D plots to investigate the properties of the materials based on the material constitutions and the experimental conditions. They reported that a well-trained ANN could model the wear and that the results of the model were in good agreement with the computed results. Aleksendric and Duboka [9] used ANN method to predict the automotive friction material features at room temperature. Five different types of friction materials were fabricated and experimented for the prediction purpose and the ANN was trained with five different learning algorithms. They found that each learning algorithm performed differently from one another but concluded that Bayesian regularization algorithm produced the best result with a single layer. Aleksendric and Duboka [10] applied the ANN to look into the possibilities of prediction wear property of friction composites at elevated temperature. They reported that ANN was effective in prediction the wear behavior of the materials as its results were in good agreement with the experimental ones. Jiang et al. [11] predicted wear and mechanical properties of polyamide composites, Varade and Kharde [12] predicted the wear behavior of PTFE glass-fiber reinforced composite using ANN and Taguchi technique. They found that ANN performed better than that of conventional Taguchi method.

Mesbahi, Semnani and Khorasani [13] employed adaptive neuro fuzzy inference system (ANFIS) to investigate the specific wear loss of PTFE, graphite short carbon fiber and nano-TiO2. They reported that ANFIS model performed better than ANN model. Jarrah, Al-Assaf and El Kadi [14] used ANFIS to model the fatigue property of unidirectional glass/fiber epoxy composite subjected to tension-tension and tension-compression conditions. They reported that the results of the ANFIS model were better when compared to those of ANN technique. Vassilopoulos and Bedi [15] applied ANFIS to model and predict the fatigue behavior of multidirectional laminate composite. They reported that about 50% of the data was adequate to model and predict the fatigue behavior of the composite and the results were in agreement with the actual data.

From above, it can be established that ANN and ANFIS models, hold great potentials and are promising tools in the modeling of complex and nonlinear wear behavior of polymer-based composites. The aim of this study is to model and predict the specific wear rate (SWR) of polytetraflouroethylene (PTFE) reinforced with glass, carbon and bronze fibers. The results of the ANN and ANFIS models were then compared with multilinear regression (MLR) model to affirm their superiority to traditional curve fit.

2. Methodology

ANN and ANFIS models have exhibited great power in describing complex, noisy and nonlinear phenomenon like specific wear rate. In this study, specific wear rate of PTFE composites was modeled and predicted using ANN, ANFIS and MLR models with density, volume fraction, sliding distance, sliding speed and load as inputs while specific wear rate as output. PTFE is a synthetic flouropolymer of tetrafluoroethylene that possesses superior characteristics due to its molecular structure consisting of fluorine and carbon. PTFE is hydrophobic and exhibits low wear resistance because of its soft nature making its suitable for use as a single material for practical application [16]. Glass fiber (GF) is a material consisting of several fine fibers of glass. GF is less brittle, less strong and cheaper than carbon. GF is compatible with most of the synthetic resin, does not rot and remain unaffected by the action of rodents and insects. Carbon fiber (CF) is composed of thin, strong crystalline filament of carbon and has a diameter of about 5–10 μm in diameter. It is very strong, stiff, and light; its strength is five times that of steel and twice as stiff. When CF is added to polymer, it improves the tribological property of the polymer [17]. Bronze fiber (BF) is a metal fiber that consists of 88% of copper and 12% of tin. It is hard and brittle. Its properties depend on the composition of the alloying tin.

A total of 63 specific wear rate experimental dataset was collected from the works conducted by [18, 19]. Some mechanical and physical properties of the materials are as shown in **Table 1**.

2.1 Artificial neural network (ANN)

ANN is a computational technique based on mimicking the function of the biological neurons [20]. Three properties are employed in differentiating various ANN models which are learning algorithms, transfer function as well as network

PTFE +Filler	Color	TS (MPa)	FS (%)	ρ (gcm^3)
Bronze fiber	Brown	18.0	165	3.90
Glass fiber	White	19.5	235	2.10
Carbon fiber	Black	13.5	87	2.25

Table 1.
Some physical and mechanical properties of the PTFE reinforced composites.

architecture [21]. The principal parts of ANN are the nodes or neuron which process the data and the interconnections that show the interconnection power connected to numeric weights [21, 22]. **Figure 1** shows the input, hidden and output layers of ANN architecture [23]. The fundamental structure of the neuron is as indicated in **Figure 2**. Each neuron receives input data, assigns weight $w_i$to the input data that indicates the connection power for that input data for each connection. Thereafter, a bias b_i value is added to the total addition of the input data and corresponding weights (u) in accordance with (Eq. (1)).:

$$u_i = \sum_{j=1}^{N} w_i x_j + b_i \tag{1}$$

where x_i is the input data, j is the jth data, w_i represents the weight, b_i shows the bias and N stands for the total number of the data points.

The summation is transformed into output with the aid of a transfer (an activation) function $F(u_i)$, generating a value referred to as the unit's "activation", as provided in the (Eq. (2)).

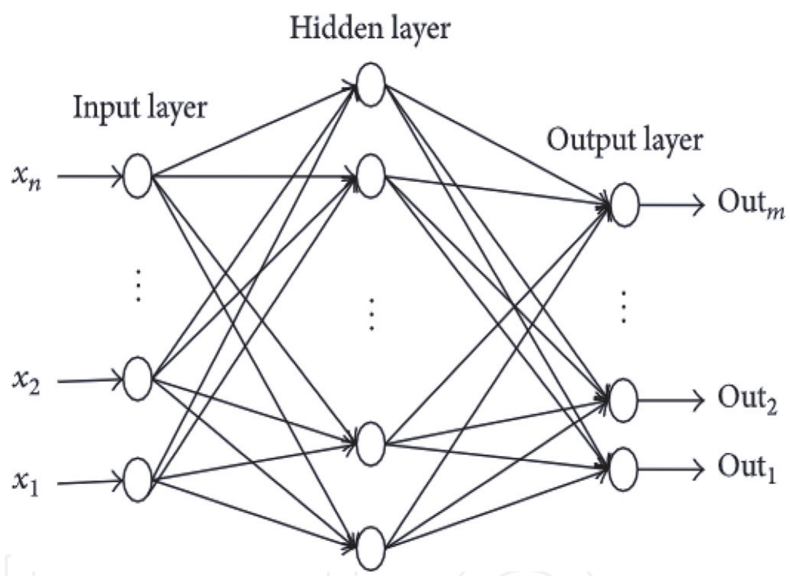

Figure 1.
A classical ANN image.

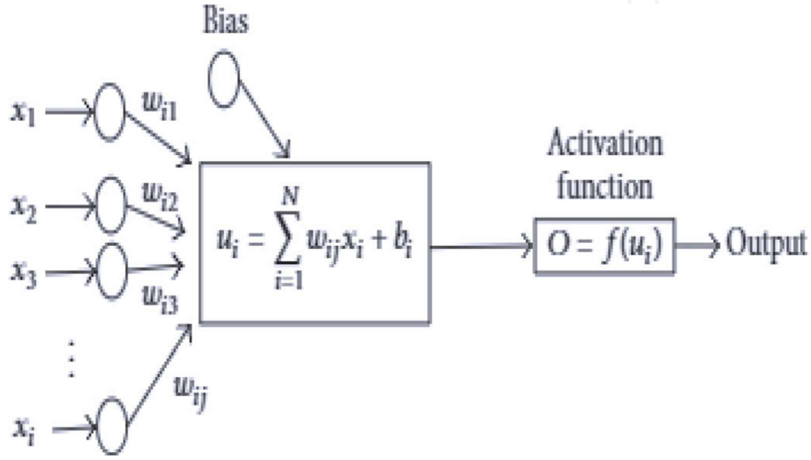

Figure 2.
The fundamental configuration of an artificial neuron.

$$O = f(u_i) \tag{2}$$

where O is the output.

One of the common types of ANN is the feed-forward neural network (FFNN). In FFNN technique, the processing layer is completely interrelated by weights to the rest of the processing layers (neurons). The learning stage in FFNN is actualized by back-propagation (BP) algorithm. The idea of using the BP algorithm is to compute the optimum weights that lead to the production of the target data in accordance with a chosen accuracy. In this paper, FFNN was applied due to its unique superiority of generating exclusive solutions without any prior knowledge of the mathematical computations in the parameters. **Figure 3** shows the architecture of a FFNN used in this study. The ability of ANN to learn by example makes it suitable for solving complex and nonlinear behavior such as specific wear rate that cannot be addressed by conventional mathematical or physical models [24].

2.2 Adaptive neuro fuzzy inference system (ANFIS)

ANFIS is an important neurological network technique to obtain result of function approximation questions integrating the adaptive neural network and fuzzy inference system. As a global estimator, ANFIS was designed to surmount the limitations of FIZ and ANN. ANFIS integrates the experience capability of neurological network and the merits of the rule-based fuzzy structure, which can assimilate previous information into categorization mechanism. A structure is constructed by fuzzy logic descriptions as well as the neurological network is utilized to harmonize the structure variables naturally thus removing the demand for manual perfection of the fuzzy structure variables not like the neurological network where the structure is constructed by training. Adaptive ability and flexibleness of ANFIS makes it effective in handling the unpredictability of processes. The ANFIS architecture is made up of five different layers arranged like any multiple layer FFNN; coded in accordance with their operational functions. Sugeno firs-order fuzzy model had been applied in this paper. Different from ANN whereby weights are attuned, determination of the fuzzy language rules is needed as training the ANFIS model. The training of the membership function variables of the ANFIS is actualized through back propagation and/or least square and variables of the Takagi

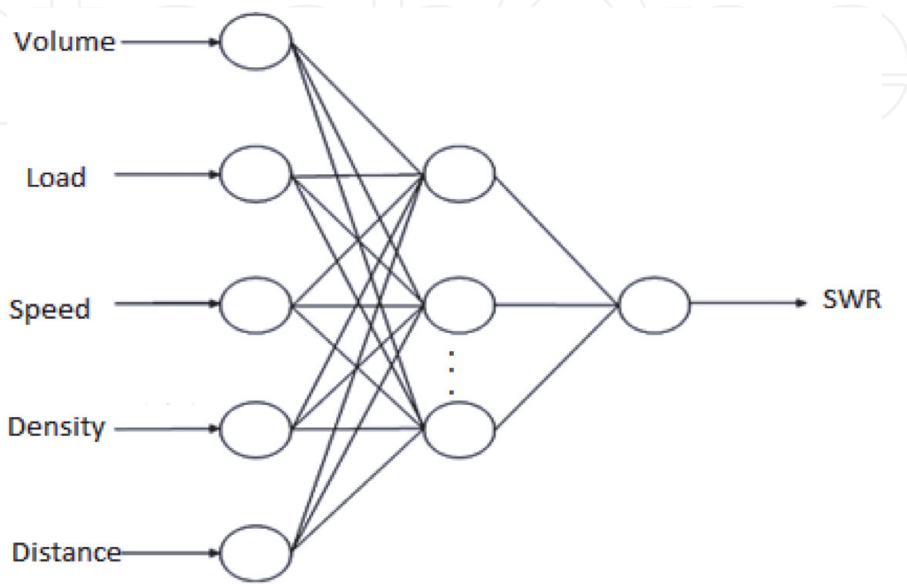

Figure 3.
ANFIS and first-order Sugeno FIS model configuration.

Sugeno fuzzy model are trained by the conventional square technique. The overall output of the ANFIS structure is described as a linear combination of the consequent variables. The common representation of an ANFIS model is demonstrated in **Figure 4** using two input variables.

Supposing fuzzy inference system with two inputs and one output as x, y and f, a Sugeno fuzzy first order, the rules are thus:

$$\text{Rule (1)}: \text{If } \mu(x)\ A_1 \text{ and } \mu(y) \text{is } B_1; \text{then } f_1 = p_1x + q_1y + r_1 \tag{3}$$

$$\text{Rule (2)}: \text{If } \mu(x)\ A_2 \text{ and } \mu(y) \text{is } B_2; \text{then } f_2 = p_2x + q_2y + r_2 \tag{4}$$

Membership functions parameters for x and y inputs are A_1,B_1, A_2, B_2 outlet functions' parameters of f are p_1, q_1, r_1, p_2, q_2, r_2, a five-layer neurological network arrangement possess the expression and configuration of ANFIS as:

First layer: Every node I is an adaptive node in this layer that contain the nodal function as:

$$\psi_i^1 = \mu_{Ai}(x) \text{ for } i = 1, 2 \text{ or } \psi_i^1 = \mu_{Bi}(x) \text{ for } i = 3, 4 \tag{5}$$

Where ψ_i^1 is for input x or y is the membership grade. Gaussian membership function had been selected in this paper because of its minimum prediction error.

Second layer: T-norm operator links every rule in this layer between inputs 'AND' operator thus:

$$\psi_i^2 = \beta_i = \mu_{Ai}(x) \times \mu_{Bi}(x) \text{ for } i = 1, 2 \tag{6}$$

Third layer: "Normalized firing strength" is the output of this layer:

$$\psi_i^3 = \varpi = \frac{W_i}{W_1 + W_2} \quad i = 1, 2 \tag{7}$$

Fourth layer: Each node i in the fourth layer is an adaptive node and executes the consequent of the rules as follows:

$$\psi_i^4 = \varpi(p_ix + q_iy + r_i) \tag{8}$$

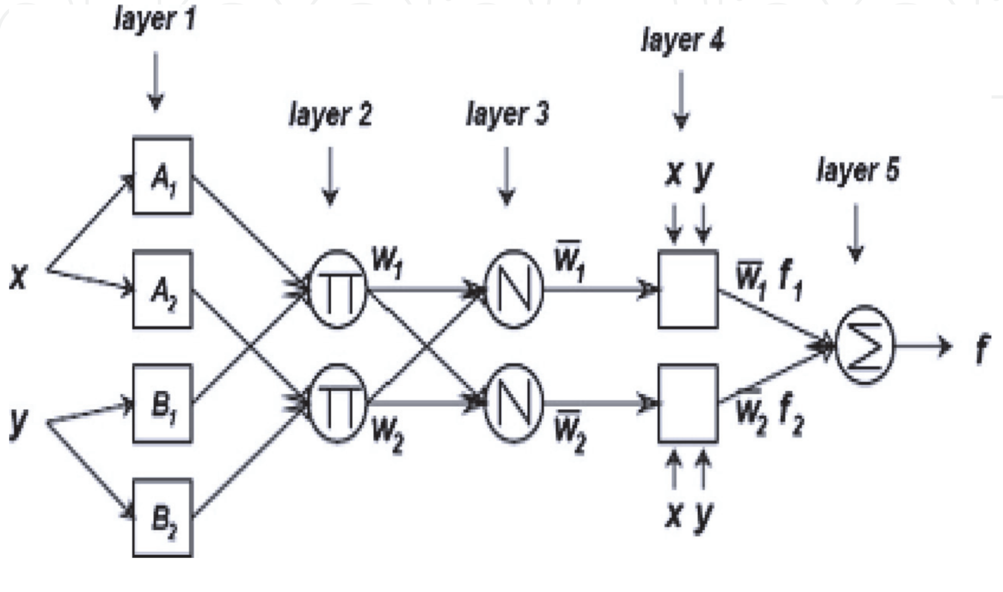

Figure 4.
ANFIS and first-order Sugeno FIS model configuration.

ϖ describes the output of layer 3 and p_i, q_i, $r_1$are the consequent parameters.

Layer 5: Here the overall output of all incoming signals is calculated in this layer as:

$$\psi_i^5 = \varpi(p_i x + q_i y + r_1) = \sum w_i f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{9}$$

2.3 Multi linear regression (MLR) model

Linear regression analysis is a conventional technique used in applied science fields to describe and examine different parameters. Regression analysis especially aids in comprehending how the standard values of the dependent parameter varies as independent parameters vary, whilst the other independent parameters are held constant; examines the correlation between these parameters. The equation below was obtained from the regression analysis.

$$SWR = 0.162 + 0.269L + 0.369D - 0.293\rho + 0.347V + 0.0417S \tag{10}$$

where SWR is the (specific wear rate), L = applied load, D = sliding distance, ρ = density, V volume fraction of reinforcement and S = sliding speed.

2.3.1 Sensitivity analysis

In order to find the parameter that greatly influences the specific wear rate of the composites, nonlinear sensitivity analysis was conducted using neural network. In the sensitivity analysis each of the input parameter was used to predict the specific wear rate of the composites through the FFNN model. The performance of the individual model was assessed based on training and testing stages of the modeling. The mean value of the prediction performance criterion of each model obtained in both training and testing phases was then used to rank the contribution of the parameters to the specific wear rate of the composites.

2.3.2 Data pre-processing and performance evaluation

The data used in this study was normalized between zero (0) and unity (1) using the (Eq. (11)). The normalization was done to prevent bigger data values from overshadowing the smaller ones. Besides, data normalization simplifies the numerical computations in the model which in turn improves the prediction quality of the model and reduces the time taken to achieve global minimum.

$$\lambda_{norm} = \frac{\lambda - \lambda_{min}}{\lambda_{max} - \lambda_{min}} \tag{11}$$

Where $\lambda_{norm}$is the normalized mass loss value, λ_{min}, and λ_{max} represent actual, minimum and maximum mass loss values of the data, respectively.

The data was split into training data and testing data. The training data was used to adjust the weights of all the linking neurons until the required error level was attained. Consequently, the network performance is evaluated by using the testing data. The prediction performance is determined using Nush-Scutcliffe or determination coefficient (DC) and root mean square error (RMSE). DC indicates fitness of the observed data and lies between -∞ to 1 while RMSE measures the difference between actual and predicted values and ranges from 0 to 1. Higher B and lower RMSE indicate efficient model and vice versa. DC and RMSE are given in (Eq. (12)). and (Eq. (13))., respectively.

$$DC = 1 - \frac{\sum_{i=1}^{n} \left(\lambda_{acti} - \lambda_{predi}\right)^2}{\sum_{i=1}^{n} \left(\lambda_{acti} - \overline{\lambda}_{acti}\right)^2} \quad (12)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(\lambda_{acti} - \lambda_{predi}\right)^2}{N}} \quad (13)$$

Where N is number of observations, λ_{acti} stands for actual values, λ_{predi} represents the predicted values and $\overline{\lambda}_{acti}$ is the mean value of the actual values.

3. Results

3.1 Performances of the models

This section discusses the results obtained from the modeling of the study. The ANN, ANFIS and MLR models were also compared. **Table 2** showed the performance of the models.

3.2 Performance of the multilinear regression (MLR) model

In the MLR model, the data was split into two subclasses of training and testing. The ratios of the training and testing phases were characterized based on the fact that the common configuration of the model was built with respect to training data set. Hence, the quantity of data in the training category plays an important function. The total number of data was 63 in which 70% (44) and 30% (18) were randomly selected for training and testing, respectively. **Figure 5** shows the scatter plot of the relationship between actual and predicted specific wear rate (SWR) of the PTFE composites.

As it was shown in **Figure 5**, the determination coefficient (DC) of the training and testing phases were determined as 0.5674 and 0.5267, respectively. In addition, the RMSE in training was found to be 0.1275 but the testing stage RMSE was computed as 0.2306. As per the prediction analysis the DC and RMSE in the testing phase were considered. Therefore, MLR model with a DC of 0.5267 and RMSE of 0.2306 did not indicate higher prediction accuracy of the specific wear rate of the PTFE reinforced composites. This is attributed to the nonlinearity and complex nature of specific wear rate of the composites and MLR model is commonly good at finding linear and non-complex relationship between predictor and response variables [25].

Model	Training		Validation		Testing	
	DC	RMSE	DC	RMSE	DC	RMSE
MLR	0.5674	0.1275	—	—	0.5266	0.2306
FFNN	0.9847	0.0341	0.9837	0.031	0.9749	0.0559
ANFIS	0.9847	0.0231	0.9956	0.025	0.9971	0.0168

Table 2.
Performance results of the models.

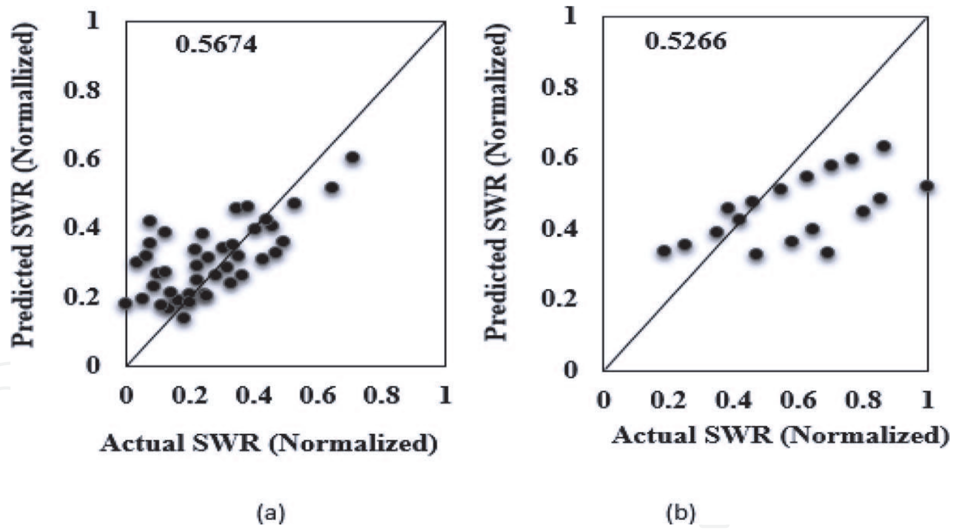

Figure 5.
Scatter plot of MLR model in (a) training and (b) testing stages.

3.3 Performance of the feed forward neural network (FFNN) model

Various learning algorithms were tried in order to find the optimum FFNN architecture and among all of them, Levenberg–Marquardt was found to be the most effective. In the FFNN model, the data is categorized into three subsets of training, validation and testing. The ratios of training, validation and testing are characterized based on the fact that fundamental architecture of the FFNN model is built based on the training data set. The whole data of the specific wear rate measurement was 63 in which 44 (70%) was chosen for training, 9 (15%) was selected for validation and 9 (15%) was chosen for testing. Besides, the sigmoid tangent was selected as the transfer function. The ANN model was trained with a single hidden layer. In addition, the number of neurons in the hidden layer was approximated using (Eq. (6)). [26] instead of performing trial and error approach.

$$N_h \leq 2x_i + 1 \tag{14}$$

where N_h stands for the maximum number of neurons in the hidden layer and x_i equals the number of predictors. Therefore, in this research, based on the predictors which were five (5), the maximum number of neurons in the hidden layer was computed as eleven (11). The optimized ANN architecture with a single layer was thus expressed as [5–11-1]1.

Figure 6(a), **(b)**, and **(c)** shows the scatter plot of FFNN model in training, validation and testing stages, respectively. As seen in **Figure 6(a)** and **(b)** the FFNN model exhibited desirable results in both training and validation phases. Additionally, to estimate the prediction performance of the FFNN model, the DC was evaluated for the testing step as shown in the scatter plot of **Figure 6(c)**. As indicated in **Figure 6(c)**, the DC for testing of the FFNN model was determined as 0.9749 with a RMSE of 0.0559. This means that an FFNN model is more efficient in predicting the wear behavior of the composites, as compared to MLR model. This result was similar but higher than the previous study [27]. To round off, ANN model was found to be efficient in predicting the specific wear rate of the composites. This tallies with past studies of [28–29].

3.4 Performance of the adaptive neuro fuzzy inference system (ANFIS) model

In this study, ANFIS that used the hybrid learning algorithm was employed. The proportions training, validation and testing were chosen the same as the ones in

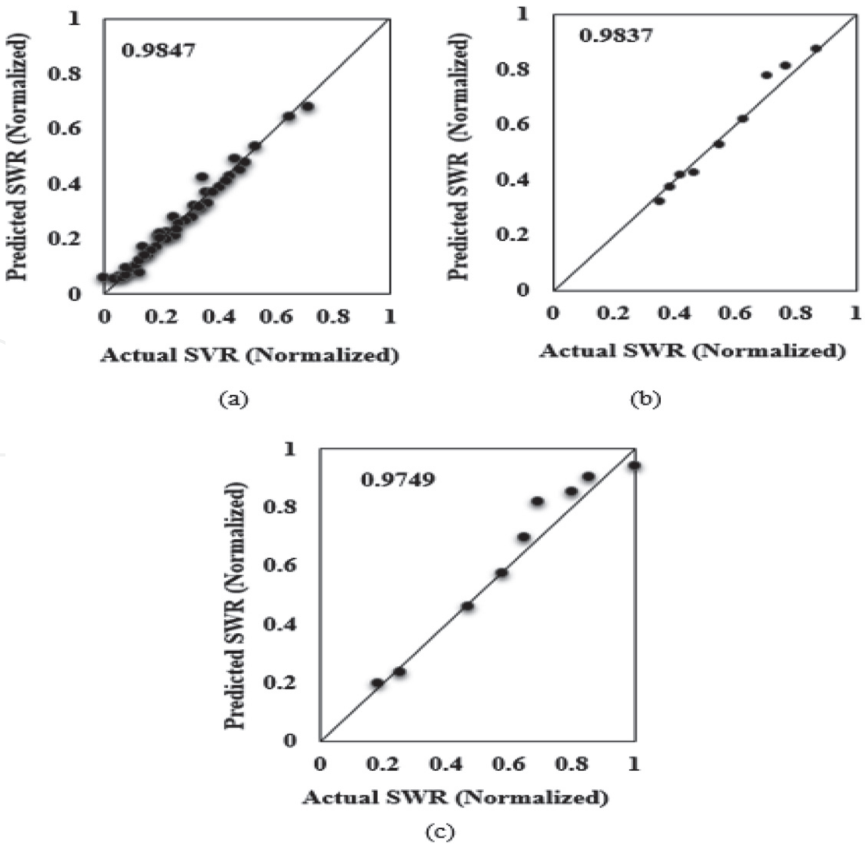

Figure 6.
Scatter plot of FFNN model in (a) training (b) validation and (c) testing phases.

FFNN modeling. To determine the best membership function, trial and error approach was used and it was found that Gaussian membership function gave the best results at 50 epochs and 0.05 tolerance errors. **Figure 7** shows the scatter plot of the relationship between the actual and predicted specific wear rate of the composites training, validation and testing stages. **Figure 7** shows perfect coincidence of the target and the output data which demonstrated the capability of the ANFIS model. As it was indicated in the figure, the DC of the ANFIS in the testing stage was computed as 0.9971. More so, the RMSE was computed as 0.0225. To wrap up, ANFIS model was found to be capable of approximating the specific wear rate of the composites with satisfactory performance. This excellent performance of the ANFIS model agrees with the research by [30–31].

3.5 Comparing the results of FFNN, ANFIS and MLR models

In this article, the performance of FFNN, ANFIS and MLR models on predicting the specific wear rate of PTFE composites based on determination coefficient (DC) and root mean square error (RMSE) was investigated. The higher values of DC and lower values of RMSE indicate better and accurate prediction capability of model. For the purpose of the comparison, the data was split into 65% (40) and 35% (22) in training and testing, respectively for all the models. The comparative results of the models were shown in **Table 3** above. As seen in **Table 3**, the performances of the FFNN and ANFIS models were better than that of the MLR model. FFNN and ANFIS models outperformed the performance of the MLR model by 43.14% and 43.12% and 48.23% and 50.02% in training and testing phases, respectively. In other words, the prediction quality of MLR model was ineffective compared to the high prediction quality of ANN and ANFIS of 0.9783 and 0.9961, respectively. Their

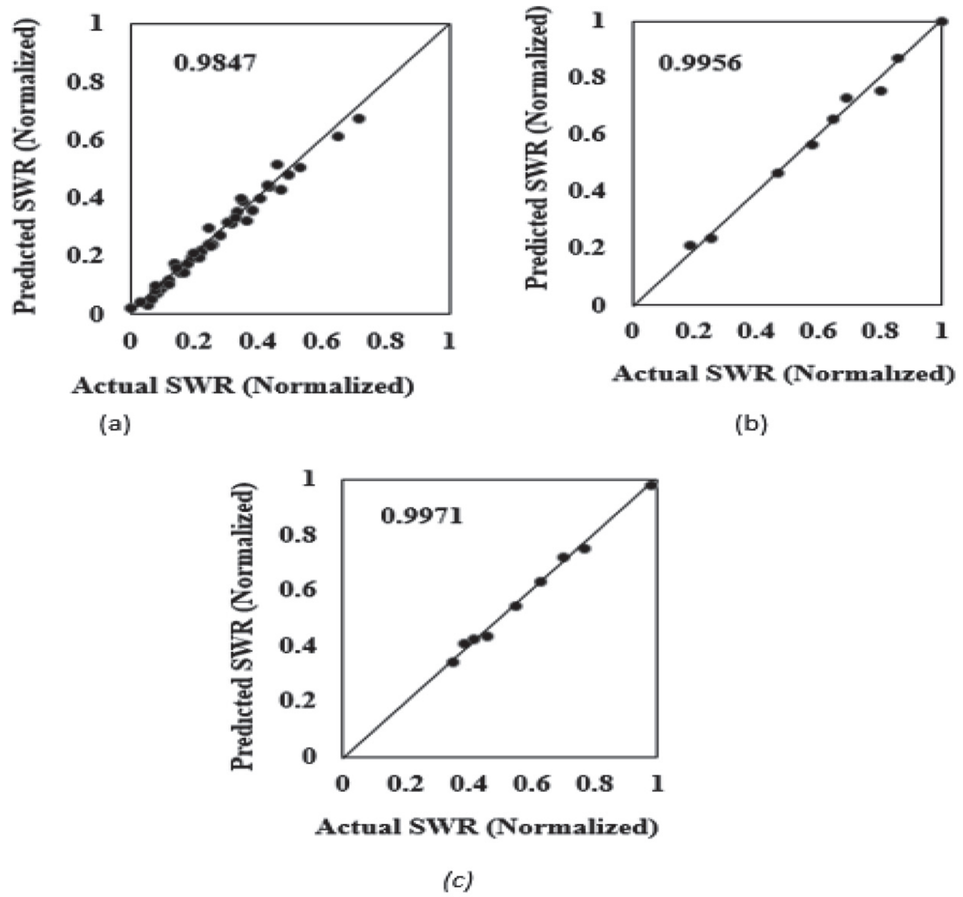

Figure 7.
Scatter plot of ANFIS model in (a) training (b) validation and (c) testing.

Model	Training		Testing	
	DC	RMSE	DC	RMSE
ANFIS	0.9841	0.0249	0.9961	0.0186
FFNN	0.9843	0.0248	0.9783	0.0441
MLR	0.5529	0.1314	0.4959	0.2067

Table 3.
Comparative performance results of the models.

capabilities to predict the specific wear rate with minimum errors of 4% and 2% (within acceptable level) as compared to the high error of MLR model of 21% is associated with their abilities to deal with nonlinear, noisy, complex relationship and to learn from outside environment and generalize. More so, the prediction performance of the ANFIS model was slightly higher than that of ANN model by 2%. This is because ANFIS model combines the attributes of both learning algorithm and fuzzy logic structure. **Figures 8** and **9** show the scatter plot of the models prediction quality and the simulated prediction results, respectively. It can be seen that ANFIS and FFNN models indicated perfect match with the actual SWR of composites while MLR model exhibited imperfect consistency with respect to the observed SWR of the composites.

3.6 Sensitivity analysis

Identification of most influential parameter in the study of wear is a significant step in achieving optimum results. In the light of this, a nonlinear FFNN sensitivity

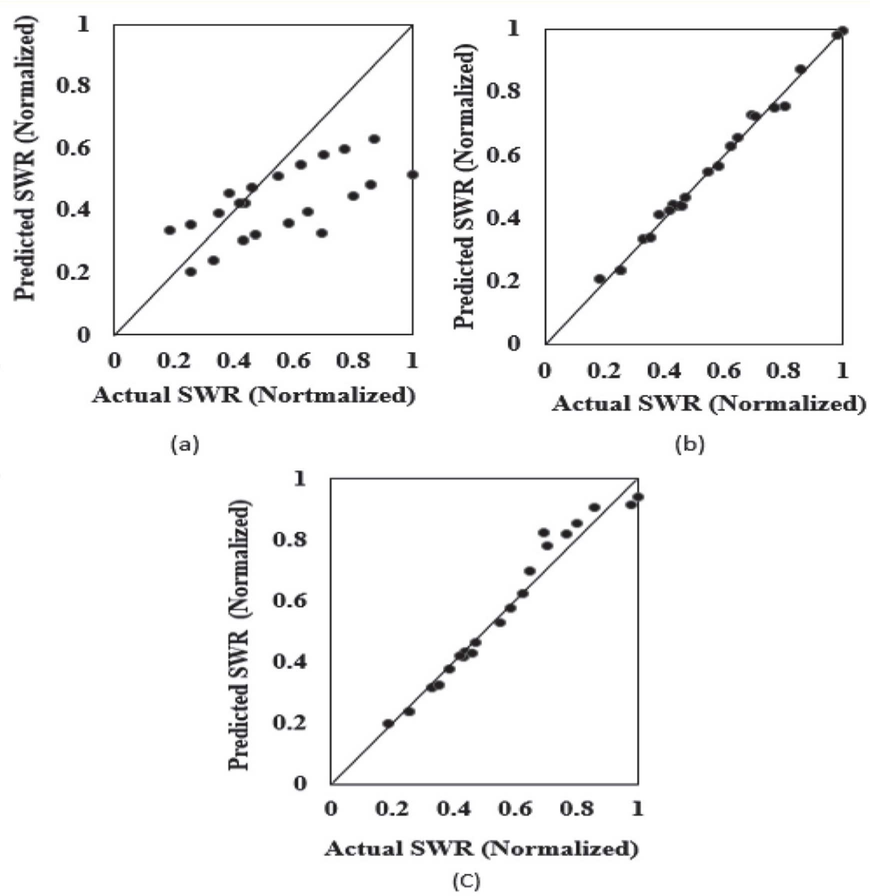

Figure 8.
Scatter plot of (a) MLR, (b) ANFIS and (c) FFNN models in testing stages.

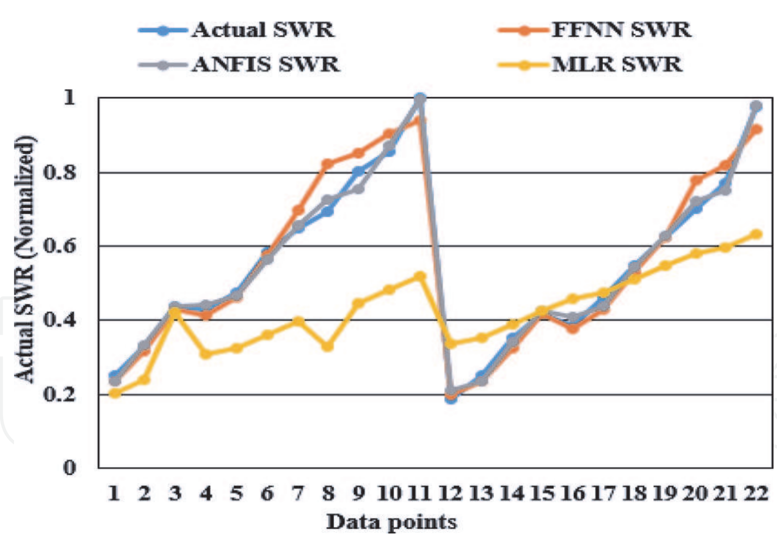

Figure 9.
Comparing the performance of the models: Testing stage.

of the specific wear rate of the composites was applied in this study to establish the dominant parameters in place of using traditional linear methods. The five specific wear rate were evaluated and ranked based on the mean value of the DC of the single modeling obtained in training and testing phases of the FFNN modeling. The results of the ranking based on the sensitivity analysis of the specific wear rate was presented in **Table 4**.

As seen from **Table 4**, in terms of the experimental conditions sliding distance is the most influential parameter, then sliding speed and the least was the applied load. On the contrary [27] reported that the sliding speed had the greatest effect on

Parameter	Average DC	Rank
Volume fraction	0.4658	1
Density	0.4027	2
Sliding distance	0.3503	3
Sliding speed	0.2985	4
Applied load	0.1476	5

Table 4.
Sensitivity analysis results of each input parameter.

Output ANFIS Model		FFNN Model		MLR Model	
SWR t-stat	t-critical	t-stat	t-critical	t-stat	t-critical
0.3464	1.6702	−0.4492	0.3464	0.4701	1.6702

Table 5.
Results of t-test at 5% significance level.

the volume loss of the polymer composites. This means that the various sliding distances can lead to different specific wear rate of the composites. The higher the applied load the more the composites will spend in the elastic deformation phases. With respect to the composites constitutions, volume fraction of the reinforcements had the greatest effect on the specific wear rate followed by density. This implies that as the volume fraction of the reinforcing phases was increased hardness with a corresponding increase in density that minimizes the specific wear rate of the composites. This agrees with the work of [13]. However, when all the parameters are compared it was found that volume fraction was the most influential and applied load presented the least effect on the specific wear rate of the composites.

The model's goodness of fit versus the actual values for the ANN and ANFIS models was tested using t-test at 5% level of significance and the outcomes revealed that there was no significance difference between the predicted and the actual values of the SWR. This was as shown in **Figures 6** and **7** and the t-test result was presented in **Table 5**.

4. Conclusions

In this study, three various data driven models namely: feed forward neural network (FFNN), adaptive neuro fuzzy inference system (ANFIS) and multi linear regression (MLR) were applied in modeling and prediction of the specific wear rate (SWR) of polytetraflouroethylene (PFTE) composites. MLR model with DC of 0.5266 and RMSE of 0.2306 was found to be inefficient enough to predict the SWR of the composites. This is due to the complex and nonlinear relationship between the investigated variables and MLR model is usually good at establishing linear relationship between predictors and responses. FFNN model having DC equals 0.9802 and RMSE as 0.0471 was found to be capable in predicting the SWR of the PTFE reinforced composites. ANFIS model DC equal to 0.9967 was found to be talented in approximating the SWR of the composites. FFNN and ANFIS models were found to be highly qualitative in predicting the SWR of the composites, yet MLR model was found to be incapable in the same prediction scenario. The high prediction performance of the FFNN and ANFIS models is owing to their capability to deal with nonlinear, noisy and complex relationship which is typical of SWR of the polymer composites. Although, both ANFIS and FFNN models were capable of predicting the SWR of the composites, ANFIS was found to be more efficient in predicting the SWR of the composites than FFNN model. The sensitivity analysis of the built FFNN model indicated that sliding distance was the dominant parameter on the SWR of the composites in terms of the experimental conditions while volume fraction of the reinforcing phases was also influential parameter on the SWR with respect to the composites compositions. However, considering all the input parameters volume fraction of the reinforcements was the most dominant parameter and applied load was the least parameter influencing the SWR of the PTFE composites. The goodness of fit was rechecked using t-test at 5% significance level and the results affirmed the superiority of the FFNN and ANFIS models as powerful and efficient tools of modeling and prediction of SWR of the PTFE composites.

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Conflict of interest

The authors declare no conflict of any kind.

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