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Prediction of abrasive wear behavior of the poly-tetra-fluoroethylene material using adaptive neuro fuzzy interface systems

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KEYWORDS

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ANFIS
Pin on disc
Fuzzy logic
PTFE
Wear

ABSTRACT

The process of estimating wear rates for composites is nonlinear and complex. Artificial intelligence (AI)-based expert systems, such as artificial neural networks (ANNs) and fuzzy inference systems (FIS), possess several useful characteristics that make them suitable for modeling nonlinear systems. However, the accuracy of the ANN prediction is hindered if the input variables are unexpectedly altered. The Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the adaptability and learnability of ANNs with the verbal expressions of the FIS. This study proposes an ANFIS sub-clustering-based prediction model for the abrasive wear rate of Polytetrafluoroethylene (PTFE), which is widely used in various applications. The experimental wear of the PTFE material was estimated by varying the load, speed, and sliding distance using in-house tribometer, and the extracted data was used to design an ANFIS model for wear prediction. The designed model was tested on a dataset that was not used to build the model. The regression analysis of the proposed model exhibited high prediction capability, with an R2 value of 0.999 and a mean squared error of 0.39%.

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1.0 INTRODUCTION

Soft computing technologies used regularly in the engineering business for evaluating important features include artificial neural networks and fuzzy logic circuits. This is due to the fact that these computer models can read a wide variety of challenging issues at a much lower operational cost than standard arithmetic models. Wear can occur for a variety of reasons, including adhesive, abrasive, fatigue, and fretting. The toughness or performance of composites, coatings, tools, aerospace crafts, bone, and hip implants, and automotive parts is significantly impacted by abrasive wear. Wear is often studied experimentally (Bowden,1986) due to the wide variety of process variables that might affect it, including sliding distance, speed, material properties, and surface roughness. For the purpose of investigating wear analysis, numerous mathematical modeling strategies have been proposed. To investigate wear analysis, several mathematical modeling strategies have been proposed (Popov et al., 2007; Vakis et al., 2018) These methods include continuum mechanics (Johnson, 1985; Hills and Nowell, 1994), analysis (Goryacheva, 1998; Barber, 2018), stochastic (Nayak, 1971), multidimensional (Li et al.,2004), atomic and molecular kinetics (Bhushan et al.,1995), finite element modelling (Yevtushenko and Grzes, 2010), boundary element system (Xu and Jackson, 2019), dimension reduction method (Argatov and Fadin , 2010), and symptom modelling (Ali et al., 2014; Bucholz et al., 2014). However, due to the complexity of surface phenomena, the understanding of them through mathematical modeling is still somewhat limited.

The use of AI in tribology has become increasingly common in recent years. Jones et al., 1997 used artificial neural networks to simulate wear patterns and forecast durability statistics. Artificial neural networks accurately forecast wear behavior and provide a time-saving alternative to traditional testing methods. Among the many areas where this method has been put to use are the following: polymer composite wear (Friedrich et al., 2002; Jiang et al., 2007; El Kadi, 2006; Veltan et al.,2000), tool wear (Quiza et al., 2008), on-line wear rating (Ghasempoor et al.,1998), brake performance (Aleksendrić , 2009 and Bao et al., 2012), polymer corrosion (Jiang and Zhang, 2012), wheel and rail wear (Shebani and Iwnicki, 2012), the wear rate of copper-aluminum nano-composites (Fathy and Megahed, 2012), and the wear rate of heat-treated aluminum-clay composites (Agbeleye et al., 2018). Bhaumik et al., 2019 devised a method for determining the friction coefficient with different friction modifiers. Argatov and Chai, 2012, recently utilized this method to estimate sliding wear. Similarly, Dhande et al., 2021, employed ANN and RSM techniques to predict abrasive wear.

ANN prediction models save time, money, and resources by cutting down on the number of experiments that need to be done. But, when input variables are unexpectedly changed, the pattern recognition ability of the ANN can be compromised, leading to inaccurate or unpredictable results. In some cases, the ANN may even converge to a very large negative or positive peak value, leading to an interpolation issue. Fuzzy rules, which can be developed separately, can be used to limit the rate of change in nonlinear behavior. Referring to ANNs in this way can help us fine-tune our membership criteria and guidelines (MFs). A Fuzzy Inference System (FIS) is responsible for linking inputs with outcomes. An ANFIS is based on the structure of a first-order Takagi-Sugeno (T-S) type fuzzy inference system (Nguyen et al., 2002). Without learning capabilities, FIS cannot select the best network design that minimizes the output error cost function. The MFs of the structure are then fine-tuned using artificial neural networks with several layers (Jagtap and Pillai, 2014). Because of its adaptability and capacity for learning, ANFIS can combine the linguistic abilities of FIS with those of ANNs.

The ANFIS is an accurate artificial intelligence (AI) method for modelling the characterization of dry surface contacts, as demonstrated by its evaluation of wear between alloyed steel and reinforced plastic (Vlădăreanu et al., 2018). In this study, FISs for the ANFIS model are generated using three distinct optimization strategies: sub-clustering, fuzzy c-means, and grid partitioning. To accurately model the wear behavior of a certain material, such as hardened steel, a predictive AI model can be used. While ANFIS, FIS, and ANNs all performed admirably in accuracy tests, ANNs ultimately emerged as the best solution (Alambeigi et al., 2016). For evaluating the wear behavior of GFRP composites under various concentrations of materials and speeds, Yilmaz et al., 2022 proposed a prediction model based on ANFIS sub-clustering. Gangwar et al., 2021recently used ANFIS to assess the wear characteristics of a boron carbide and molybdenum disulfide reinforced matrix. The proposed ANFIS model found the optimum concentrations and operating conditions to achieve the lowest wear.

This research aims to quantify the abrasive wear that occurs during sliding under different conditions of load, speed, and sliding distance. Experimental results and estimating models for ANNs are often compared in the existing literature. The literature on the use of ANFIS for predicting wear rate is scarce, though. Wear behavior prediction of polytetrafluoroethylene (PTFE) under various loads, sliding distances, and speeds is proposed using a sub-clustering-based prediction model.

2.0 METHODOLOGY

2.1 Experimental Work

The measurements were carried out using an in-house tribometer, following ASTM G99 standards (Figure 1). The testing system consisted of a vertically fixed pin and a horizontally rotating circular disc, with the cylindrical pin (30mm length, 8mm diameter) as the research specimen (Figure 2). The pin was made from Polytetrafluoroethylene (PTFE) and its material properties are listed in Table 1. The disc was prepared by slicing a rod with an initial diameter of 140mm into 11mm slices, and its surface was finished with 600-grit sandpaper. The pin was kept in contact with the disc under a constant load, applied by a pin carrying the weight of the arm. Prior to each test, both the pin and disc were cleaned. The disc was rotated by a PMDC motor controlled by a speed-control unit, which included a thermistor-driven potentiometer and an AC to DC power transformer.

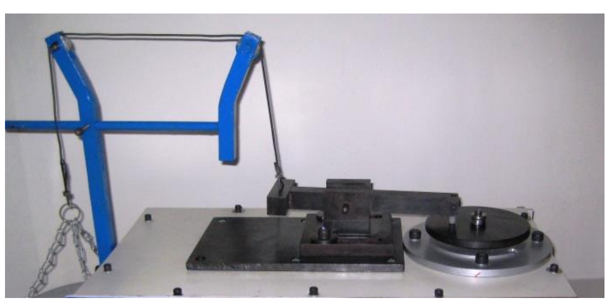

Figure 1: Experimental test setup.

Figure 2: Specimen PTFE cylindrical pin.

Table1: Material properties of PTFE.

Property	Value
Specific gravity	2.15 g/cm^3
Elasticity modulus	490-600 Mpa
Coefficient of friction	0.06-0.1
Thermal conductivity	0.251 W/(m.K)
Hardness	50-65 (Type D)

The volumetric wear of the pin was determined using a digital scale (TAPSON 200T, resolution of 0.1mg), while length loss was determined using a micrometer (resolution of 0.02mm). The device was checked for accuracy before and after each test. The volume loss of the pin was estimated using an empirical relation (equation 1), which relates the initial and final sample weights and the sample density, where W_1 is the initial sample weight, W_2 is the final sample weight, and ρ is the sample density.

$$\text{Wear volume (V)} = \frac{W_1 - W_2}{\rho} \tag{1}$$

The tests were conducted in dry conditions with various input parameters, including load, sliding speed, and sliding distance, as shown in Table 2. The tests were repeated three times, with the average of the results used for analysis. The normal load was varied from 4.905N (0.5 kg) to 24.525N (2.5kg) to achieve significant weight loss. The sliding velocity was independently determined by varying the radius of the sliding track, ranging from 0.125m/s to 2.7m/s. An increase in temperature was observed with increasing sliding distance, but no actual temperature measurements were taken.

Table 2: Test Parameters.

Parameter	**Value(s)**
Normal load (N)	4.905, 9.81, 14.715,19.620, 24.525
Disk speed (RPM)	250, 500, 750, 1000, 1250
Sliding velocity (m/s)	0.125 to 2.70
Wear track radius (mm)	25 to 60
Pin material	PTFE
Disk material	Mild Steel

2.2 ANFIS Structure

The ANFIS is one of the most well-known examples of a hybrid intelligent neuro-fuzzy inference structure (Jang, J.-S. R., 1993) and it employs a five-layer architecture to learn relationships between input and output data and then use those relationships to determine the optimal distribution of membership functions (MFs). Figure 3 depicts the ANFIS's overall layout and functionality. Each tier has several nodes, each of which has its own node function. The nodes with static parameter settings (circles) are contrasted with the adaptive nodes (squares), where the settings are subject to change. The output data from this layer's nodes will be the input for the subsequent layer.

The fuzzy interface system (z) constitutes two inputs (x, y) and one output (z). In a first order Sugeno fuzzy model, the typical if-then rules are as follows:

$$\text{If } x \text{ is } P_1 \text{ and } y \text{ is } Q_1, \text{then } f_1 = m_1 x + n_1 y + c_1 \tag{2}$$

$$\text{If } x \text{ is } P_2 \text{ and } y \text{ is } Q_2, \text{then } f_2 = m_2 x + n_2 y + c_2 \tag{3}$$

where P_1, P_2, Q_1, Q_2 denote membership values of input variables (x , y) ; and m_1, n_1, c_1, and m_2, n_2, c_2 are parameters of the output function f_1 and f_2, respectively, also called the consequential parameters. The structure is built with the following layers:

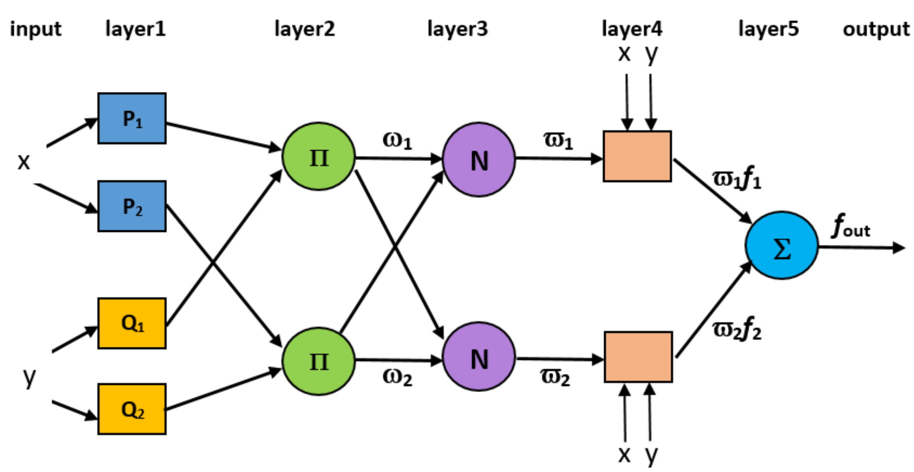

Figure 3: ANFIS structure.

Layer 1: An individual variable in the input language is represented by one of the adaptable nodes in the first layer. Following is a definition of the node function:

$$O_{1,i} = \mu_{Ai}(x) \text{ for } \mathrm{i}=1,2 \tag{4}$$

$$O_{1,i} = \mu_{B-2}(y) \text{ for } \mathrm{i}=3,4 \tag{5}$$

In this case, the output of the ith node in the Nth layer is denoted by O_n,i, where P_i or Q_j is the linguistic label. The x and y variables are the inputs to the node. Assuming a Gaussian function is used for the MF here:

$$\mu_{A_i(x)} = \exp\left\{-\left(\frac{x-c_i}{a_i}\right)^2\right\} \tag{6}$$

where $\{a_i, c_i\}$ are the appropriate parameters for the variable Gaussian function. The types and numbers of membership functions affect the premise parameters, which are also called first-layer parameters.

Layer 2: As shown in Figure 1, the nodes of the second layer are all represented by circles and are fixed. The strength of the next layer's firing is calculated by multiplying the input signals by this factor.

$$O_{2,i} = \mu_{Ai}(x)\, \mu_{Bi}(y) = \omega_i \text{ for } \mathrm{i}=1,2 \tag{7}$$

where the output, ωi, represents the rule's efficacy in triggering an action.

Layer 3: Every node in the third layer (also called the normalized layer) is shown in Figure 1 as a circle labelled "N," indicating that it is a fixed node. Normalized firing strength at a node can be calculated by dividing its firing strength by the total number of rules.

$$O_{3,i} = \frac{\omega_i}{\sum \omega_i} = \frac{\omega_i}{\omega_1 + \omega_2} = \varpi_i \quad for\, i=1,2 \tag{8}$$

Layer 4: As shown in Figure 1, every single node is an adaptive node in this layer. Following is a description of the node's function.

$$O_{4,i} = \varpi_i f_i \quad \text{for } \mathrm{i}=1,2 \tag{9}$$

where fi represents the fuzzy if-then rules given by (1) and (2).

Layer 5: The final layer consists of fixed nodes whose sole purpose is to add up the signals at their inputs.

$$O_{5,i} = \sum \varpi_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} = f_{out} \tag{10}$$

where fout is the result that was inferred by the ANFIS. The sum of the errors in the provided training data for this ANFIS multilayer network (with n entries) is determined by the formula:

$$E = \sum_{i=1}^{n} E_i = \sum_{i=1}^{n} \left(T_i - f_{out_i}\right)^2 \tag{11}$$

Where, Ti is the expected result of the ith entry, fouti is the result of operating the ANFIS on the ith entry, and Ei is the error for the ith entry in the given training data set. The ANFIS output fouti is a linear combination of the consequent parameters {mi, ni, ci} if the premise parameter {ai, ci} is in a steady state, as shown below (Jang J-SR, 1993; Jang J-SR, Chuen-Tsai, 1995):

Where Ti is the target value for the ith entry, fouti is the value obtained after implementing the ANFIS to it, and Ei is the error for the ith entry in the given training data set. If the premise parameters {ai, ci} are in a steady state, as shown below, the ANFIS output fouti is a linear combination of the consequent parameters {mi, ni, ci}.

$$\begin{aligned} f_{out} &= \sum_{i=1}^{2} \varpi_i f_i = \varpi_1 f_1 + \varpi_2 f_2 \\ &= \varpi_1 (m_1 x + n_1 y + c_1) + \varpi_1 (m_2 x + n_2 y + c_2) \\ &= (\varpi_1 x) m_1 + (\varpi_1 y) n_1 y + \varpi_1 c_1 + (\varpi_2 x) m_2 + (\varpi_2 y) n_2 y + \varpi_2 c_2 \end{aligned} \tag{12}$$

The matrices are expressed as follows when Eq. (11) is provided with N training data:

$$f = \begin{bmatrix} f_{out1} \\ f_{out2} \\ . \\ . \\ . \\ f_{outn} \end{bmatrix}, \quad \theta = \begin{bmatrix} m_1 \\ n_1 \\ c_1 \\ m_2 \\ n_2 \\ c_2 \end{bmatrix}$$

$$B = \begin{bmatrix} \varpi_1 x_1 & \varpi_1 y_1 & \varpi_1 & \varpi_2 x_1 & \varpi_2 x_1 & \varpi_2 \\ \varpi_1 x_2 & \varpi_1 y_2 & \varpi_1 & \varpi_2 x_2 & \varpi_2 x_2 & \varpi_2 \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ \varpi_1 x_n & \varpi_1 y_n & \varpi_1 & \varpi_2 x_n & \varpi_2 x_n & \varpi_2 \end{bmatrix} \tag{13}$$

where θ represents an unidentified matrix of order M × 1, and M is the total number of parameters in the ensuing sets. If N data sets denoted by P were imported into the adaptive network, then ' f'' is a output vector of the network having size P × 1 with N elements, and B represents the vector of order P × M in this case. According to the least-squares-estimator, the equation for is as follows:

$$\theta^* = \left(B^T B\right)^{-1} B^T f \tag{14}$$

where BT is the transpose of B and B-1 is the inverse of B.

The ANFIS training algorithm was executed using Matlab R2017a's fuzzy inference toolbox to predict the abrasive wear rate. The process involves four distinct steps. Firstly, compiling an event data array that includes both input and output data. Secondly, importing the training data and verifying the results with the data provided using the ANFIS editor. The third step involves initializing the fuzzy inference system (FIS) by specifying the number and type of membership functions (MF) to be used for nonlinear function modeling. ANFIS employs a feed-forward network to discover fuzzy decision rules that perform well on the input-output data set by generating adjustable MF parameters. Since optimizing the adaptive parameter is critical to the adaptive system, this study uses the ANFIS approach that utilizes a hybrid learning algorithm that is more efficient than the traditional backpropagation algorithm in approximating the true values of the model parameters. Hybrid methods offer several benefits, including finding a good set of consequent parameters using two techniques: (i) gradient descending and (ii) the least-squares method. Subsequently, ANFIS trains the input data, and if the error tolerance between the training and testing data's output is within the required range, the training process will end automatically. Otherwise, ANFIS will revert to generating FIS until an adequate match is obtained.

2.3 Proposed ANFIS Model Development

The Fuzzy Logic Toolbox's five primary GUI tools for working with fuzzy inference systems are the Fuzzy Inference System (FIS) Editor, the Membership Function Editor, the Rule Editor, the Rule Viewer, and the Surface Viewer. If you make a modification to the FIS, it will automatically update in all other active GUIs. The dynamic linking between these interfaces makes this possible. In this investigation, a Rule-Based Mamdani-Type Fuzzy Modeling (RBMTF) strategy based on a Multi-Input-Multi-Output (MIMO) Fuzzy algorithm was used to model the tribological performance of the PTFE material in terms of wear loss. With the help of MATLAB's Fuzzy Logic Toolbox, the RBMTF was created, taking as inputs the parameters of normal load, sliding speed, and sliding distance, and producing the wear volume as an output parameter using the IF-THEN RULES. The results of the experiment were simulated using the graphical user interface (GUI) in MATLAB R2017a. The proposed MIMO fuzzy algorithm for wear performance prediction is depicted conceptually in Figure 4.

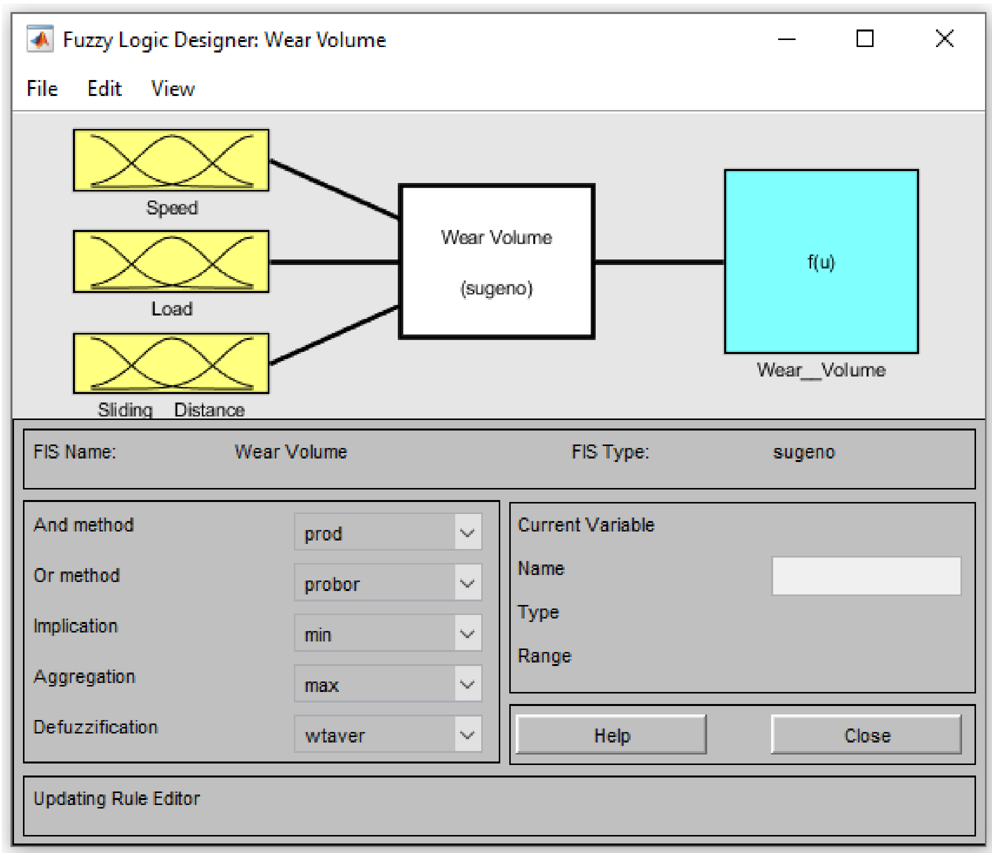

Figure 4: Proposed MIMO fuzzy algorithm.

The wear performance of PTFE material was analyzed using a MATLAB-based ANFIS model. According to Figure 5, 27 rules were written in a rule editor to improve the model's layout. The available experimental datasets' sixty input values were divided into a training set and a testing set, and then an ANFIS model for the predictions was developed. The dataset consisted of a total of 60 data points, comprising three readings for each set. Roughly 70% of the dataset (about 40 data points) was chosen at random to serve as a training as well as testing sample, while the remaining 30% (about 20 data points) was used to evaluate the performance of the ANFIS model. Additionally, the fuzzy membership function editor can be obtained by inputting the following three parameters into the view membership command on the main menu: normal load, sliding speed, and sliding distance. Inputs and outputs in this model are defined using the triangular membership function. The output is the volume of wear. Low, medium, high, and highest are the four possible values for the model's inputs, and the model's output parameter, wear volume. Table 3 lists the architecture of ANFIS and the training parameters.

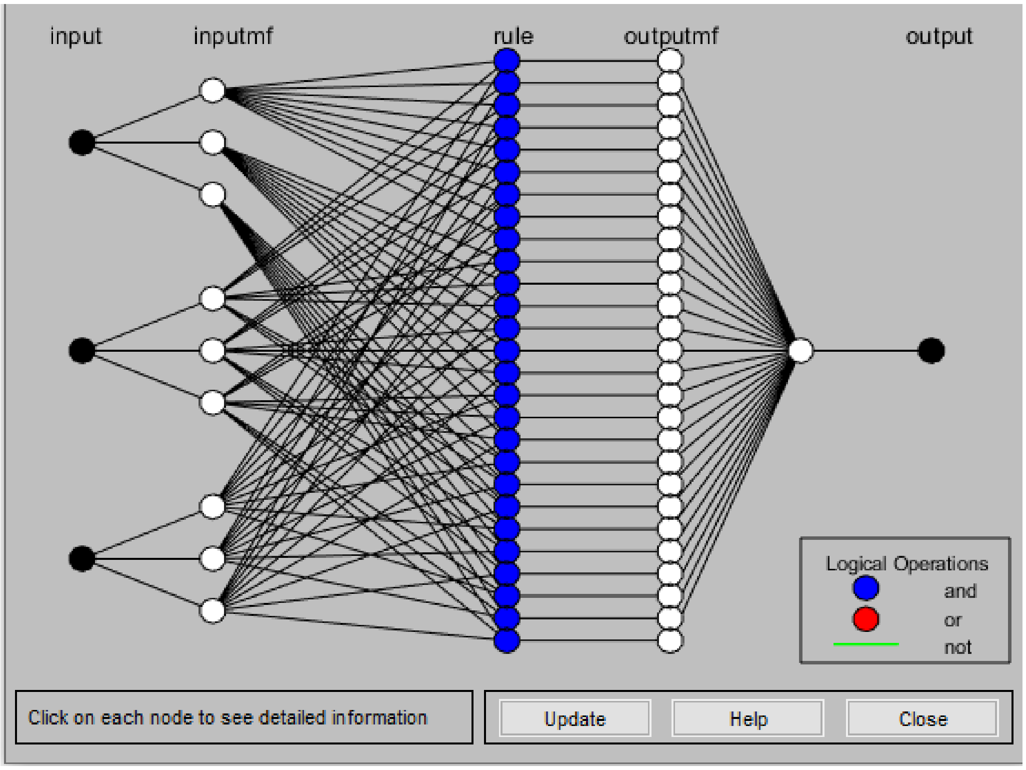

Figure 5: Proposed ANFIS model for Wear volume prediction with 3 inputs and one output.

Table 3: ANFIS Architecture and training parameters.

Number of nodes	78
Number of linear parameters	27
Number of nonlinear parameters	27
Total number of parameters	54
Number of training data pairs	20
Number of fuzzy rules	27

3.0 RESULTS AND DISCUSSION

3.1 Experimental Results

Figure 6 depicts the results of an abrasive wear volume test as a function of sliding distance and load. This dataset was used to train and validate an ANFIS model. It has been observed that the wear volume increases as the load and sliding distance increase. As the load on the pin increases, the contact area between the pin and its mating surface also increases. This increased contact area leads to higher frictional forces and pressure between the two surfaces, which can cause the pin to deform and wear out faster.

Sliding distance refers to the total distance the pin slides across its mating surface during operation. As the sliding distance increases, the duration of contact between the pin and the disc also increases. This prolonged contact causes the pin's surface to become rougher, which leads to an increase in frictional force. The increased frictional force results in an increase in wear volume over time. As the load and sliding distance both increase, the pin remains in contact with the disc for a longer duration with elevated contact pressure, resulting in increased friction forces. Therefore, with an increase in both load and sliding distance, the level of wear intensifies, as evidenced by Figure 6.

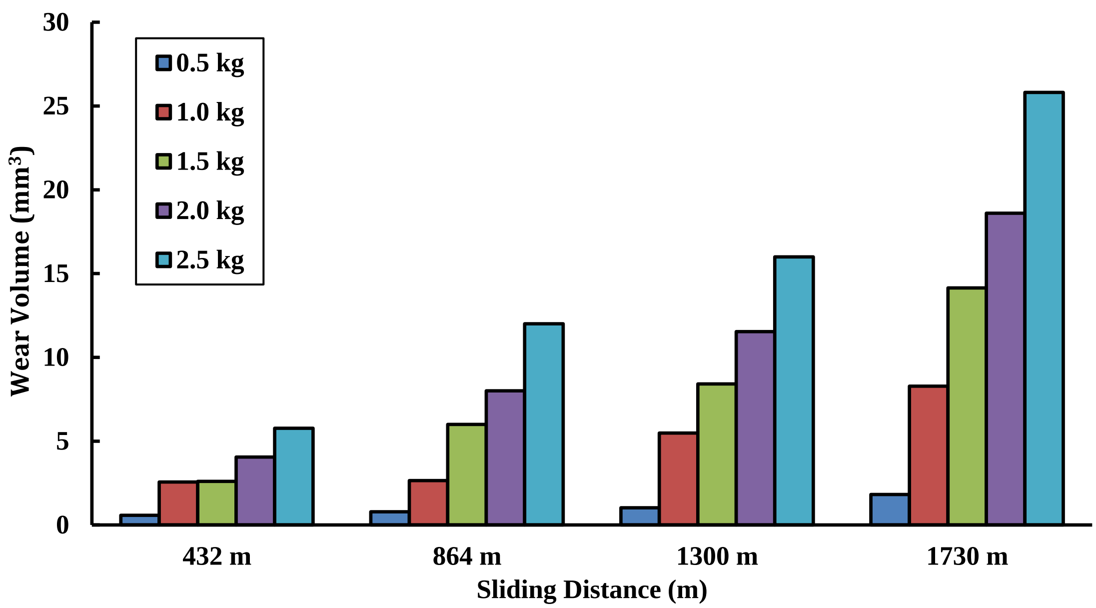

Figure 6: Variation of abrasive wear volume against sliding distance for different loads.

3.2 ANFIS Results

Figure 7 is a visual representation of the If-Then rule viewer for the wear performance, which has three inputs and one output, and the rule editor in which the twenty-seven corresponding fuzzy rules were viewed.

Utilizing the established ANFIS framework, graphs of the specific wear rate as a function of the response surface are obtained for the interaction terms. The ANFIS model's ability to predict a change in wear rate in response to variations in both speed and normal load are shown in Figure 8. It is evident that, the wear behavior of PTFE material is enhanced when a larger sliding distance is combined with a lighter normal loading condition. In this case, the lower speed (400 rpm) and higher load result in a lower wear rate. However, the wear rate increases as the speed increases. There is an initial peak in wear at maximum load (25 N), followed by a gradual decrease.

Figure 9 is a surface plot illustrating the relationship between the input parameters Load and sliding distance and the output parameter Wear volume. When the sliding distance is small (500 mm), the wear volume is small for all load values, but it grows with increasing sliding distance before levelling off. Under a load of 25 N, the wear is at its worst.

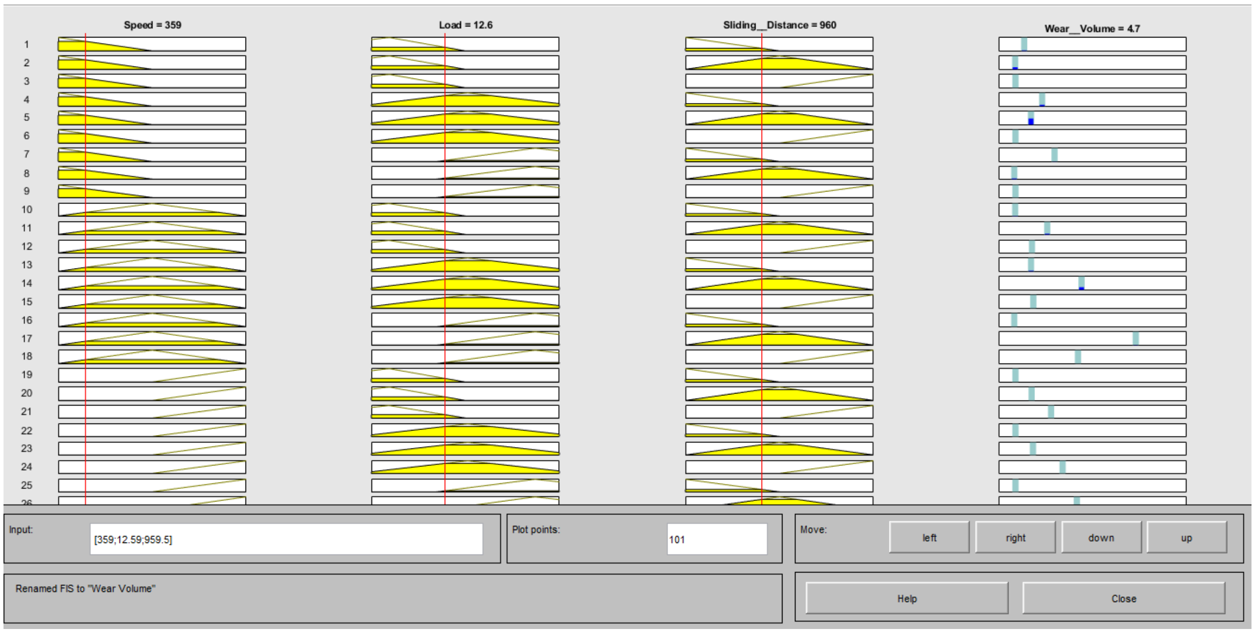

Figure 7: Prediction of the output values through if-then rule viewer for wear rate.

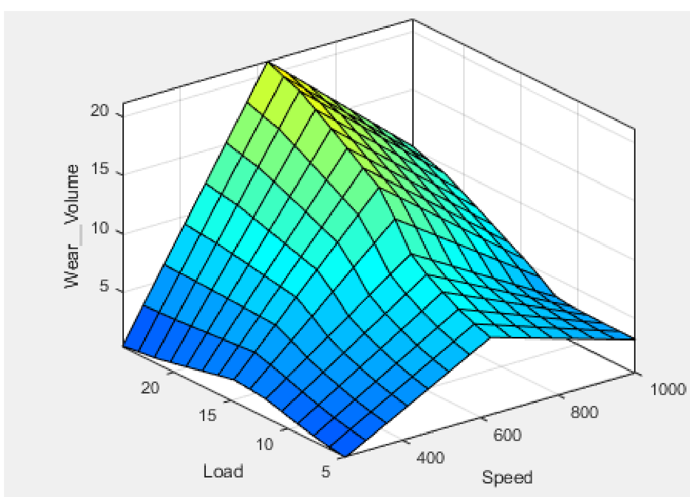

Figure 8: Surface plot for interaction between load, speed and wear volume.

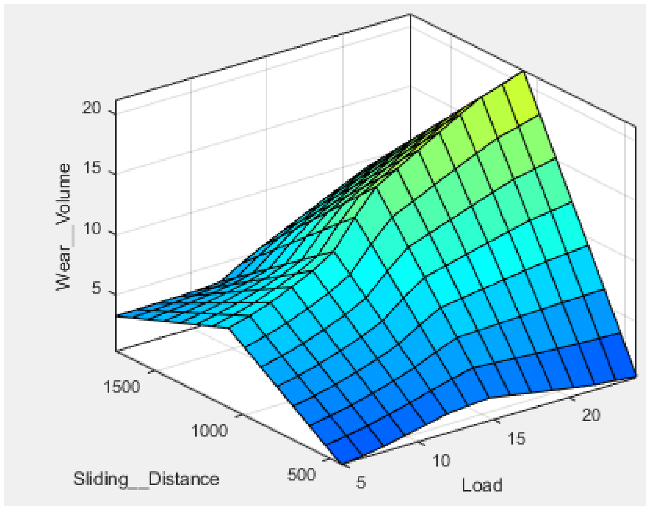

Figure 9: Surface plot for interaction between Load, Sliding distance and wear volume.

Wear loss of PTFE material is shown clearly in Figure 10 as a result of the interaction effect of sliding distance and sliding speed. The highest rotational speed (2000 rpm) and the highest wear rate are both readily apparent (1000 rpm). While wear is negligible at small sliding distances and speeds, it becomes a significant problem as both these variables are increased. It was discovered that reducing the sliding speed and increasing the sliding distance was necessary to remove the wear loss and increase the specific wear rate.

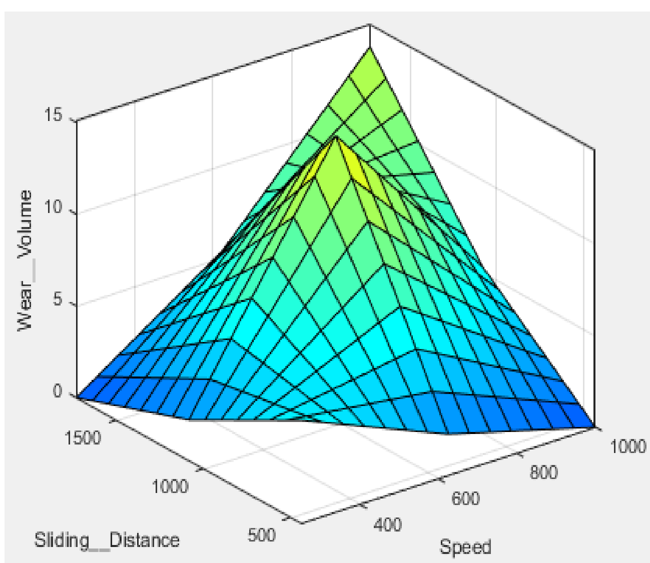

Figure 10: Surface plot for interaction between sliding distance, speed and wear volume.

It was observed that the neuro-fuzzy algorithm could predict the wear rate effectively. Table 4 compares the predicted and the experimental wear rate values for the checking data after training by ANFIS.

Table 4: Comparison of experimental and ANFIS predicted results.

Sr. No	Motor Speed (RPM)	Load (N)	Sliding Distance (m)	Expt. Wear Volume (O_E) (mm^3)	ANFIS Predicted Wear Volume, (O_P) (mm^3)	Absolute error $\lvert O_E-O_P \rvert$	Squared Error $\lvert O_E-O_P \rvert^2$
1	250	4.905	432	0.58	0.5778	0.0021	4.67E-06
2	250	9.81	432	2.56	2.6645	0.1045	0.0109
3	250	14.71	432	2.6	2.6324	0.0324	0.0010
4	250	19.62	432	4.05	4.0259	0.0240	0.0005
5	250	24.52	432	5.77	5.7792	0.0092	8.5229E-05
6	500	4.905	864	0.791	0.7926	0.0016	2.68632E-06
7	500	9.81	864	2.65	2.7066	0.0566	0.003205371
8	500	14.71	864	6	5.9379	0.0620	0.003856286
9	500	19.62	864	8	8.0711	0.0711	0.005067162
10	500	24.52	864	12	11.9726	0.0273	0.00074857
11	750	4.905	1300	1.02	1.0785	0.0585	0.003424239
12	750	9.81	1300	5.49	5.4602	0.0297	0.000885598
13	750	14.71	1300	8.42	8.6241	0.2041	0.041667424
14	750	19.62	1300	11.5	11.4628	0.0372	0.00138384
15	750	24.52	1300	16	16.0142	0.0142	0.000203063
16	1000	4.905	1730	1.81	1.7824	0.0275	0.000761484
17	1000	9.81	1730	8.28	8.3391	0.0591	0.003497658
18	1000	14.71	1730	14.1	14.0740	0.0259	0.00067496
19	1000	19.62	1730	18.6	18.5909	0.0091	8.22649E-05
20	1000	24.5	1730	25.8	25.8034	0.0034	1.20409E-05
						MSE	**0.003905807**

Figure 11 exhibits the graphical comparison between experimental and ANFIS predicted results. The R^2 value of the regression model is 0.999 which is a good indicator of accurate predictive model.

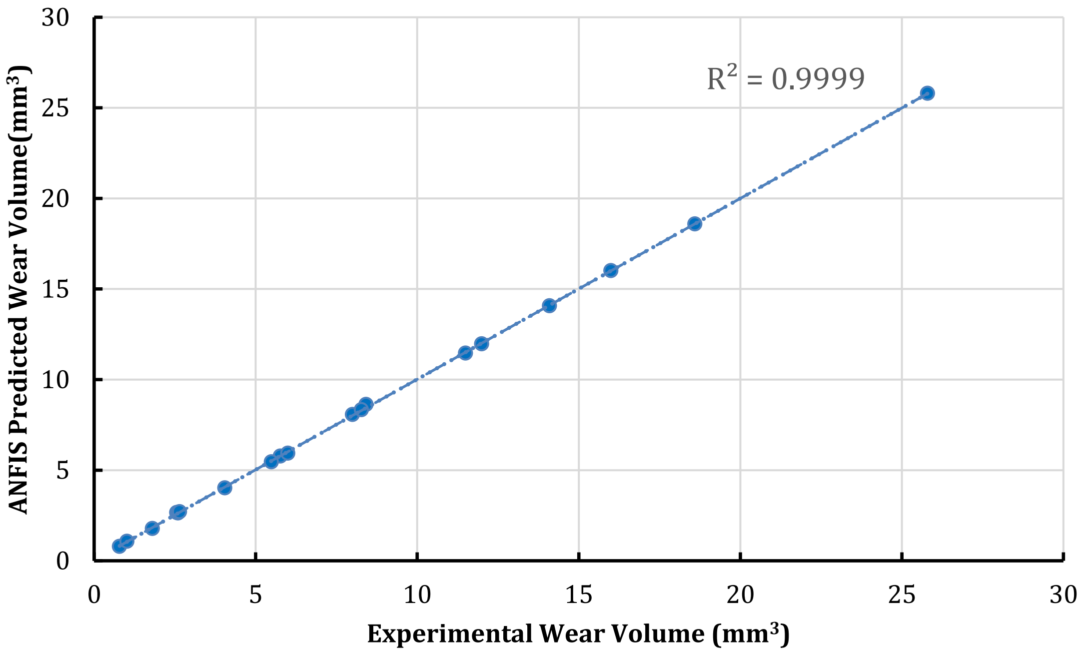

Figure 11: Graphical comparison of experimental and ANFIS predicted results.

The regression analysis is carried out by estimating mean squared error which is given by below Equation 15.

$$\text{Mean squared error (MSE)} = \frac{\sum_{i=1}^{N}(O_E - O_P)^2}{N} \tag{15}$$

As seen from Table 4, the overall mean squared error of the proposed model is 0.003905807 or 0.39%. As the value of MSE is lower, the proposed ANFIS model is performing best. Figure 11 depicts the relationship between experimental wear volume and ANFIS predicted wear volume for sample 20 data points.

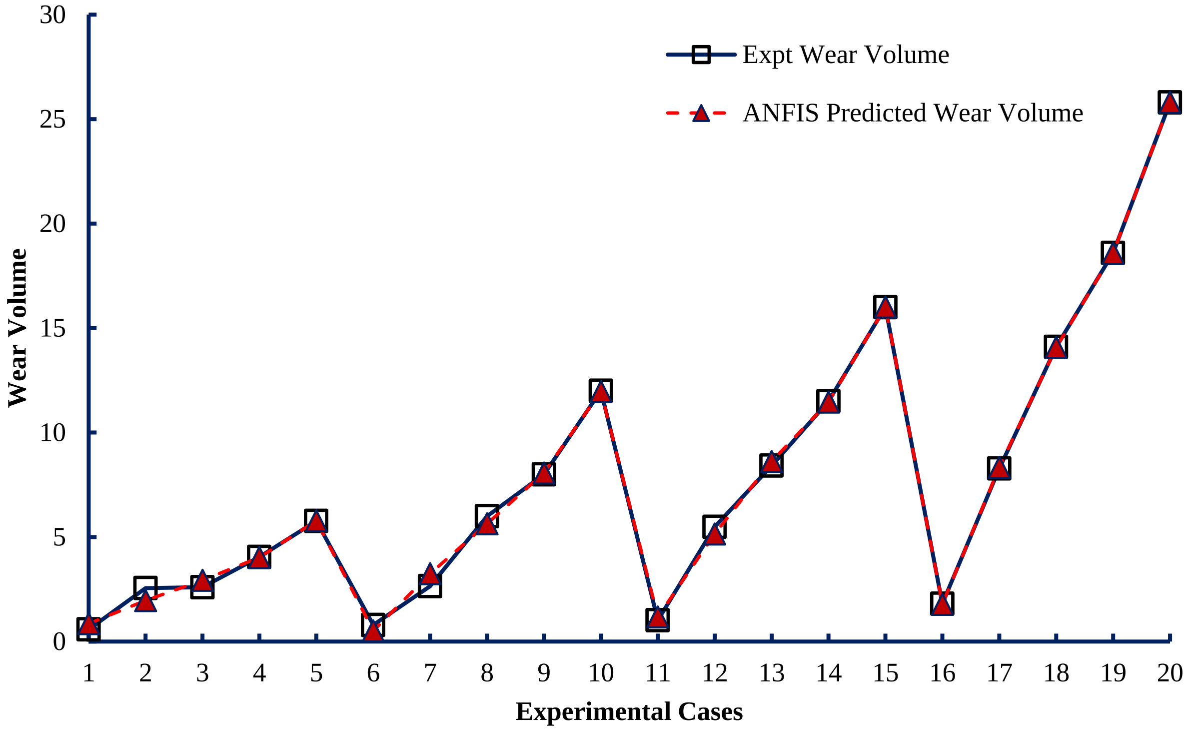

Figure 12: Comparison of experimental and ANFIS predicted wear volume.

CONCLUSIONS

In this work, an in-house Tribometer is utilized to conduct an experimental study of PTFE's tribological performance. In order to predict the wear rate for different loads, speeds, and sliding distances, an adaptive neuro-fuzzy model was developed using the collected experimental data. The following conclusions can be drawn from the analysis of the data collected and used in this study.

1. There is a direct relationship between the load, speed, and sliding distance that are inputs and the wear rate. At light loads and slow speeds, wear is reduced.
2. The specific wear rate can be predicted with a 98.99% degree of accuracy using ANFIS modelling, indicating that the predicted values of specific wear rate are in good proximity with the experimental values.
3. Finally, the response surface plot shows that the wear performance of the PTFE material can be improved by decreasing the sliding speed and normal load, respectively, to decrease wear loss.

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