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Prediction of friction and wear during ball-on-flat sliding using multiple regression and ANN: Modeling and experimental validation

Zahid Mushtaq *, M. Hanief, Suhail Ahmed Manroo

Mechanical Engineering Department, National Institute of Technology, 190006, Srinagar, INDIA.
*Corresponding author: zahidmushtaq_17@nitsri.net

KEYWORDS

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ABSTRACT

This study employs multiple regression and artificial neural network modeling techniques to predict the coefficient of friction (C.O.F) and wear during a tribological operation. A reciprocating tribometer was used to conduct ball-on-flat tribological tests on steel-steel tribo-pairs, which were lubricated with the vegetable-based jatropha oil containing molybdenum disulphide additives. A Full factorial design was used where the three input parameters (load, speed, and additive concentration) were varied at three levels, and hence a total of 27 experiments were performed. The ANN and multiple regression techniques were applied to predict C.O.F and wear, and the results were subjected to experimental validation. The ANN models were found to be the best among all models predicting the C.O.F and wear with high accuracy followed by the second-order regression models. Further mean square error (MSE), Mean absolute percentage error (MAPE), and coefficient of determination (R^2) confirms the adequacy and reliability of ANN models over the regression models. The low MSE (0.002510 and 0.001681) and MAPE (2.633 and 2.521), and high R^2 (0.995575 and 0.992261) of ANN models clearly indicate that the ANN models are capable of predicting C.O.F and wear with more accuracy and hence can be utilized for other works as well.

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1.0 INTRODUCTION

Tribology is the science and engineering of interacting surfaces that are in relative motion with each other. It comprises the processes of friction and wear, which are sometimes undesirable and result in the wastage of energy and curtailment of the life of material (Woma et al., 2019; Guo et al., 2020). Lubrication is the sure-shot-cure of this universal obstacle in order to restrict the amount of friction and wear. Lubrication can enhance the life of the machine components, save energy, and a huge amount of money to the industries (Sapawe et al., 2014; Kotia et al., 2018). Petroleum-based oils have dominated the lubricant market over the years for most of the industrial applications due to their good lubricating performance and ease in availability (Yunus et al., 2020; Talib et al., 2019). But they contribute to environmental pollution during or after their operation. Hence there is a dire need to replace the hazardous petroleum-based lubricants with environmentally friendly lubricants, and this void can be filled with vegetable oils (Syahrullail et al., 2011; Salleh et al., 2019). Amid growing environmental concerns, the vegetable oil-based bio-lubricants are acquiring more attention day by day. Their use is driven by their environmentally friendly and non-toxic nature, biodegradability, abundant availability, and regulations of the government on using petroleum-based oils (Rao et al., 2018). With the growing use of bio-lubricants, the cost of mineral oils is expected to fall (Cecilia et al., 2020). The vegetable oils are stable to extreme temperature conditions and oxidation due to the presence of anti-aging agents. They can mitigate the over-dependence on petroleum-based fossils (Owuna, 2020). They also have some unparalleled lubricating properties like high viscosity and viscosity index, low pour point, high flash point, etc (Farhanah and Syahrullail, 2015) However, the vegetable oils are having a few shortcomings which confine their direct use as a lubricant. These shortcomings can be removed, and the lubricating properties of vegetable oils can be amended by adulterating them with the proper additives. Additivation imparts special features to the vegetable oils and improves their physical properties (Chan et al., 2018). The plant jatropha has its inception from American tropical regions and is now distributed mostly in Asia and Africa. Over the years, the oil has been extracted from its seeds and used for lubrication and many other purposes (Moniruzzaman et al., 2016). Jatropha oil-based bio-lubricant has low pour point, high viscosity, high viscosity index and good stability at high temperatures. This makes it a suitable candidate for bio-lubricant applications (Attia et al., 2020). Koshy et al., (2015) reported that the addition of MoS_2 nanoparticles improved the thermo-physical and tribological properties of the coconut oil. The frictional and anti-wear characteristics of jatropha oil were boosted by MoS_2 additives (Hanief and Mushtaq, 2020).

Theoretical modeling is an essential tool nowadays and various models are being developed to predict various parameters. The accuracy of these predictions can be endorsed by comparison with the experimental data (Radovanovic and Madic, 2010). Hanief and Wani, (2016) developed ANN and regression models to predict the surface roughness during the turning of red brass. It was concluded that both the models can be used to predict roughness and ANN was found to be more accurate than the regression model. The ANN and regression models were utilized for the prediction of cutting forces in the turning of red brass. It was reported that the ANN model can predict the cutting forces more accurately than the regression model (Hanief et al., 2017). The surface roughness for running-in wear was predicted using the Gauss-Newton algorithm and ANN. The results suggested that the ANN produced slightly more accurate results (Hanief and Wani, 2015). The modeling of friction and wear has been a hot research topic over the years. The wear is a very complex phenomenon, and it is very difficult to develop a model for its accurate prediction, yet some authors have used an innovative ANN modeling for this purpose (Capitanu et al., 2019). The kinetic friction of ice was modeled and validated with the experimental data (Makkonen and Tikanmaki, 2014). Hegadekatte et al., (2008) presented a predictive model for the prediction of wear in tribometers. Gyurova and Friedrich, (2011) used the experimental data from a pin-on-disc testing machine for the training of the ANN. The trained ANN was found to predict the friction and wear with high accuracy.

This paper investigates the accuracy of ANN and regression models in predicting the friction and wear during a tribological sliding operation by comparison with the experimental data. The ball-on-flat sliding tests were conducted on a reciprocating tribometer and the Coefficient of friction between the tribo-pair was noted down. The wear of the material was calculated in terms of weight loss. Multiple-regressions and ANN models were developed and utilized for the prediction of the coefficient of friction and wear. The predicted results were plotted against the experimental results. The comparison gave the impression that both the models can predict the coefficient of friction and wear very effectively, with the ANN model being more accurate than the regression models.

2.0 EXPERIMENTAL PROCEDURE

The full factorial design of experiments (DOE) was used to select the points for the evaluation of the response. A total of 27 experiments were completed on a reciprocating tribometer with a steel-steel tribo-pair. The experimental results of some of the tests in this paper are already presented in our previous work (Mushtaq and Hanief, 2021). Then more tests were executed and added to complete a design of 27 experiments for modeling purposes. The tribo-pairs used were EN31 steel and 52100 chromium steel balls whose elemental compositions are given in Table 1. The steel slab was polished with silicon carbide emery papers of different sizes until a proper surface finish without scratches was obtained. The experimental setup of the tribometer is shown in the Figure 1. It consists of a reciprocating arm which also accompanies the ball holder. The ball holder grips the ball with the help of screws and is the moving part of the tribo-pair. While as, the steel workpiece is held fixed and stationary and the ball is pressed against it as the arm slides. The point contact between the steel slab and the steel ball is lubricated to assess the lubricating potentials of the oil.

Jatropha oil added with 20% glycerol was used as a base lubricant and the micro-sized MoS_2 as its anti-friction additive, which were retrieved from a local supplier in India. Glycerol was added in order to enhance the viscosity of jatropha oil and improve its lubricity. The MoS_2 was added to the base oil in three weight percentages (0.5, 1, and 2), and the prepared blends were placed in the ultrasonicator for enough time to allow proper mixing.

The three parameters were varied with three different values during the testing, viz, load (L), speed (S), and MoS_2 concentration (C). All the parameters were fed through the software system attached to the equipment, and the coefficient of friction at various operating conditions was evaluated. The wear scars were produced on the steel slab after each test. The steel slab was weighted on a highly accurate weighing machine before and after every test and the wear was calculated in terms of the weight loss of the material.

Table 1: Elemental composition (%) of the tribo-pair.

	C	Cr	Mn	Si	Su	P	Mo
EN-31steel	1.15	1.5	0.5	0.3	0.022	0.017	0.02
52100 Cr Steel	1.1	1.6	0.4	0.35	0.015	0.023	0.1

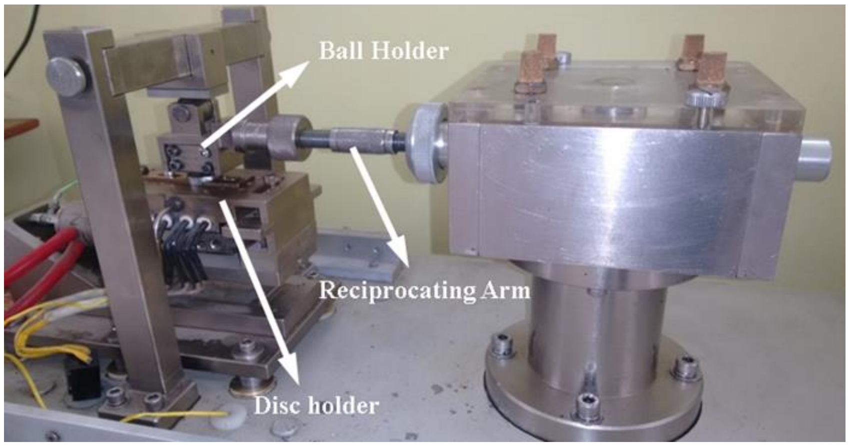

Figure 1: Experimental setup of tribometer.

2.1 Multiple-Regression Modeling for Coefficient of Friction and Wear

Multiple regression technique is mostly used for modeling experimental or categorical data (Reddy *et al.,* 2008). Therefore, it can be used in predicting the coefficient of friction and wear. In this study, two regression models are developed that relate the response variables (coefficient of friction and wear) and the predictor variables (Load (L), Speed (S), and concentration (C)). In order to predict the wear (W) and the coefficient of friction (C.O.F), the regression models can be written as

$$C.O.F = \beta_o + \beta_1.L + \beta_2.S + \beta_3.C \quad (1)$$
$$W = \beta_o + \beta_1.L + \beta_2.S + \beta_3.C \quad (2)$$
$$C.O.F = \beta_o + \beta_1.L + \beta_2.S + \beta_3.C + \beta_4.L^2 + \beta_5.S^2 + \beta_6.C^2 + \beta_7.L.S + \beta_8.L.C + \beta_9.S.C \quad (3)$$
$$W = \beta_o + \beta_1.L + \beta_2.S + \beta_3.C + \beta_4.L^2 + \beta_5.S^2 + \beta_6.C^2 + \beta_7.L.S + \beta_8.L.C + \beta_9.S.C \quad (4)$$

Where equations (1, 2) and (3, 4) represents the first order and second order regression models for the Coefficient of friction (C.O.F) and Wear respectively. While as β_1, β_2, to β_9 are the coefficients that are determined using suitable methods.

2.2 Wear and Coefficient of Friction Prediction Strategy Using Network (ANN).

The Artificial Neural Network (ANN) is generally used for forecasting, control, data compression, and for other applications such as medicine and power systems as well (Asilturk *et al.,* 2011). In a typical ANN architecture, neurons are arranged into three types of layers: an input layer, hidden layer(s) and output layer. The input layer receives inputs from the user/environment and after appropriately weighted and summed the output of the input layer is transmitted to the hidden layer(s) that further process the input data, eventually the output layer is invoked, and the result is communicated to the user/environment. The number of hidden layers and the number of neurons in each affect the output, the optimum numbers are usually chosen using hit and trial. The ANN structure used for the modeling and prediction of C.O.F and Wear is shown in figure 2. A program was written in Matlab® for the ANN model and trainbr and 'logsig' and 'purelin' functions were used for learning/training. Moreover, the data were normalized in order to avoid over-fitting or under-fitting of the network by using equation 5.

$$y_{norm} = [y_{norm}(y_{max} - y_{min}) + y_{min}] - y_{min}/(y_{max} - y_{min}) \quad (5)$$

Where
y_{norm}= scaled version of value y
y_{max}= Maximum value of data
y_{min}= Minimum value of data

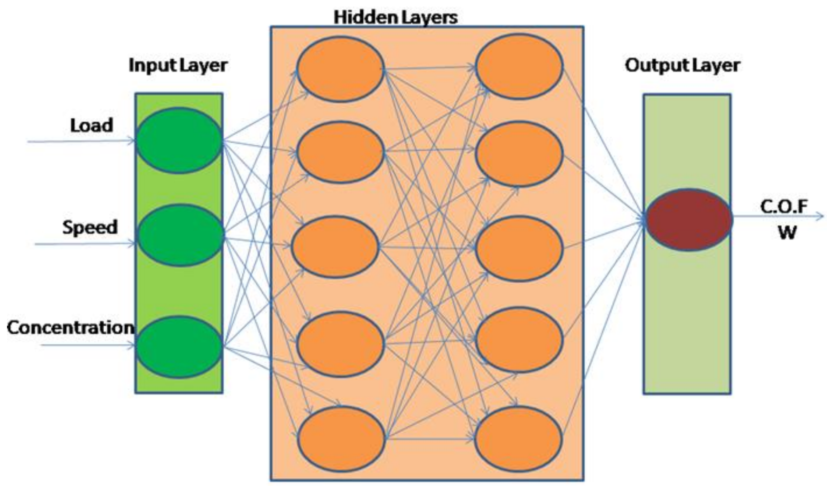

Figure 2: ANN architecture.

3.0 RESULTS AND DISCUSSION

The coefficient of friction and the weight loss (wear) values collected as a result of the experiments by varying three parameters are compiled in Table 2. Generally, it was observed that the coefficient of friction increased by increasing the load following the law of mechanics F=μR (Najar et al., 2016). However, there were some exceptions where the coefficient of friction and weight loss were lower at 100N than 50N as given in the Table 2. The coefficient of friction and wear got reduced by increasing the speed (Rpm). This may be due to the fact that at lower speeds the thickness of the lubricating film is low. At higher speeds, the film becomes thicker which restricts the metal-to-metal contact and improves the frictional characteristics. The minimum coefficient of friction (0.0264) was observed at the conditions of 2% MoS_2 concentration, 100N load and 1200 Rpm speed.

The wear scars produced on the EN-31 steel sample were examined to study the wear pattern. At lower loads, adhesive wear was observed to be the dominant mechanism. However, as the load was increased, a shift in the wear mechanism was recorded. At higher loads, a mixture of abrasive ploughing and mild adhesion wear mechanism was found on the steel scars. More adhesive pits and deep furrows were observed at higher loads. The Raman spectroscopic analysis of the steel surface before and after the sliding was conducted as shown in the Figure 3. In figure 3(a), there are no major peaks observed as the surface of the steel is clean from any impurity. However, after sliding, two major peaks can be observed at 385 cm^{-1} and 409 cm^{-1} (as shown in Figure 3b) which proves the presence of the MoS_2 micro-particles on the wear scar.

Table 2: Experimental data at different load, speed, and additive concentrations.

S. No.	MoS_2 Concentration (C) in wt.%	Load (L) in Newtons	Speed (S) in Rpm	C.O.F	Weight Loss (grams)
1	0.5	50	1000	0.0422	0.0003
2	1	50	1000	0.0389	0.0004
3	2	50	1000	0.0351	0.0003
4	0.5	100	1000	0.0623	0.0002
5	1	100	1000	0.0298	0.0001
6	2	100	1000	0.0296	0.0001
7	0.5	150	1000	0.0713	0.0003
8	1	150	1000	0.0318	0.0003
9	2	150	1000	0.0299	0.0002
10	0.5	50	1100	0.0416	0.0003
11	1	50	1100	0.0371	0.0003
12	2	50	1100	0.0334	0.0002
13	0.5	100	1100	0.0612	0.0002
14	1	100	1100	0.0280	0.0001
15	2	100	1100	0.0275	0.0001
16	0.5	150	1100	0.0693	0.0002
17	1	150	1100	0.0307	0.0003
18	2	150	1100	0.0288	0.0002
19	0.5	50	1200	0.0402	0.0002
20	1	50	1200	0.0360	0.0003
21	2	50	1200	0.0325	0.0002
22	0.5	100	1200	0.0593	0.0001
23	1	100	1200	0.0273	0.0001
24	2	100	1200	0.0264	0.0001
25	0.5	150	1200	0.0674	0.0002
26	1	150	1200	0.0289	0.0002
27	2	150	1200	0.0277	0.0001

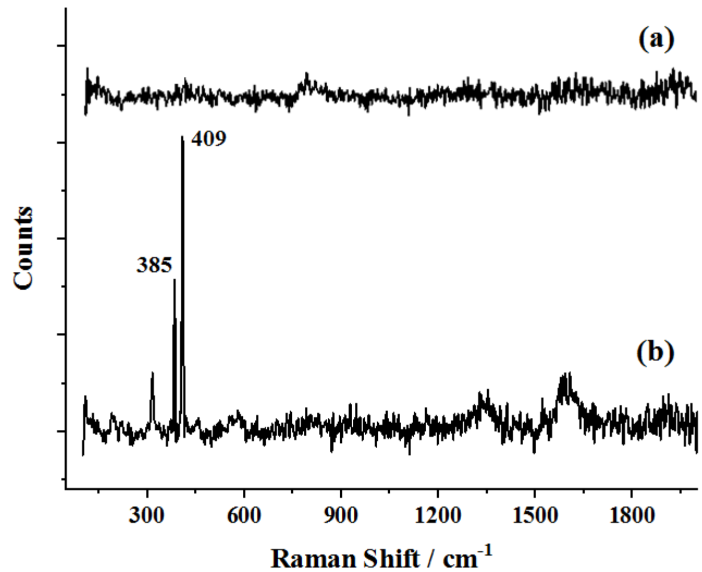

Figure 3: Raman spectrum of steel surface: (a) before sliding (b) after sliding.

3.1 Multiple-Regression Results

The experimental data shown in Table 2 was used to build multiple regression models for the coefficient of friction and wear. The coefficients β_o, β_1, to β_9 are estimated using Matlab®. Accordingly, the equations for the first-order fitted model and second-order fitted model can be written as follows:

$$C.O.F = 0.0682 + 0.0001.L - 0.00000001.S - 0.0158.C \quad (6)$$

$$W = 0.0007389 - 0.0000006.L - 0.0000004.S - 0.0000413.C \quad (7)$$

$$C.O.F = 0.0984 + 0.0002.L - 0.0000001.S - 0.0811.C + 0.00000001.L^2 + 0.000000.S^2 + 0.0322.C^2 - 0.0000001.L.S - 0.0002.L.C + 0.000001.S.C \quad (8)$$

$$W = 0.5222 - 0.0106.L + 0.0007.S + 0.0254.C + 0.0001.L^2 - 0.0000001.S^2 - 0.0593.C^2 + 0.00000001.L.S - 0.0002.L.C + 0.0001.S.C \quad (9)$$

The concentration is the most dominant factor for both wear and coefficient of friction followed by load and speed respectively. Figure 4(a,b) and Figure 5(a,b) show the comparison of experimental and predicted data for the first-order regression model and second-order regression model of wear and coefficient of friction respectively. These figures also depict a strong correlation between predicted variables and response variables. However second order regression models yield a better fit as compared to first order regression models. The adequacy of the regression model was evaluated using the statistical parameters of mean square error (MSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2), and the same is shown in Table 3. The MSE of the second-order regression model is low as compared to first-order regression model while R^2 of the second-order regression model is high as compared to the first-order regression model indicating high accuracy of second-order regression models as compared to first-order regression models.

$$MSE = 1/N \sum_{i=1}^{N} (xi - yi)^2 \quad (10)$$

$$\text{MAPE}=1/N\,\frac{\sum_{i=1}^{N}(\text{xi}-\text{yi})}{(\text{xi})}\times 100 \tag{11}$$

$$\text{R}^2=1-\left(\frac{\sum_{i=1}^{N}(\text{xi}-\text{yi})^2}{(\text{xi})^2}\right) \tag{12}$$

Where xi is the actual output and yi is the predicted output and N is the number of data points.

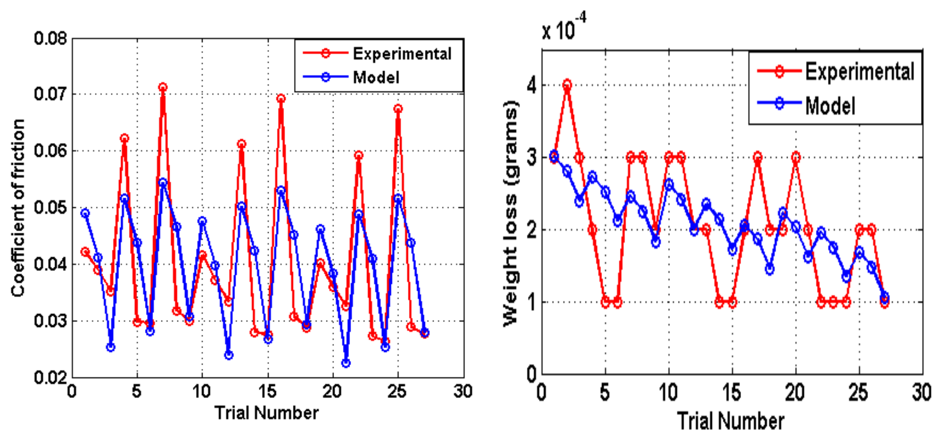

Figure 4: First-order regression models: (a) coefficient of friction and (b) Weight loss.

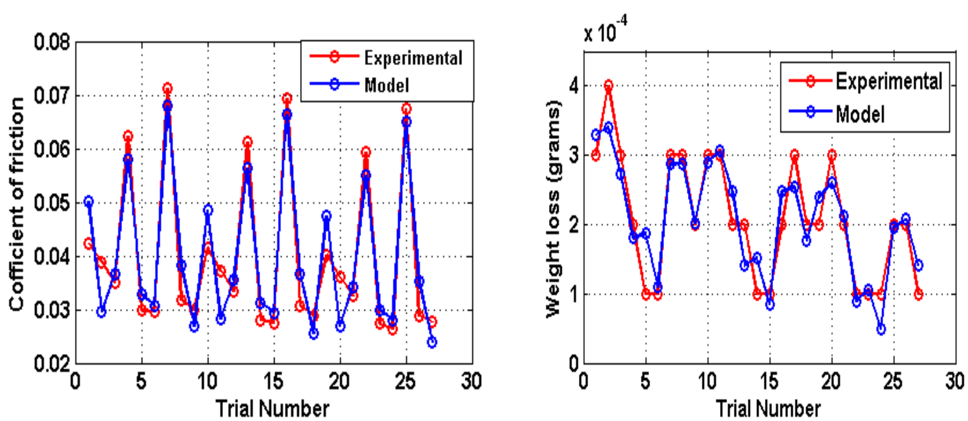

Figure 5: Second-order regression models: (a) coefficient of friction and (b) weight loss.

3.2 ANN Results

The results of ANN models are shown in Figure 6(a,b). The data set of the experimentation consists of 27 data points out of which 21 data points were used for training the network and 6 data points selected randomly were used for the testing. It can be clearly seen that ANN yields the best fit with both the training and testing datasets of friction and wear and is shown in Figure 7 and Figure 8. The results obtained were compared using statistical methods. The coefficient of determination (R^2) and MAPE as shown in Table 3 are also in acceptable ranges and depict the high accuracy of ANN models as compared to regression models.

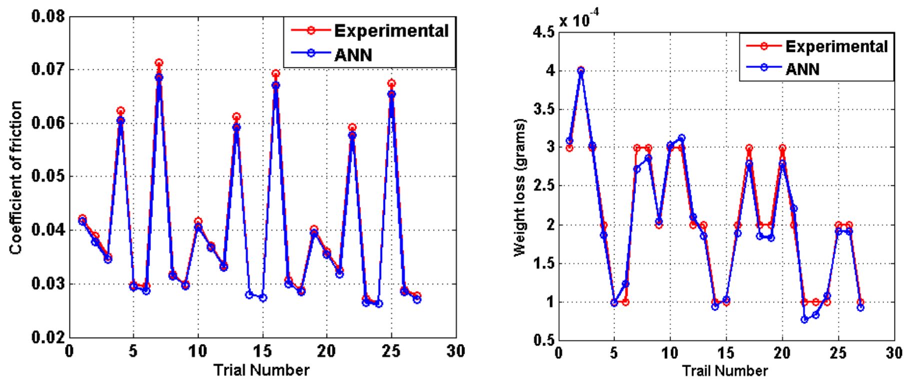

Figure 6: Results of ANN modeling for: (a) coefficient of friction and (b) weight loss.

A full factorial plan of experimentation is applied to look for the effects of load, speed, and additive concentration on the friction and wear during tribological sliding. After each tribological sliding operation, the measurements of friction and wear were observed. Multiple linear regression and artificial neural network models were used to predict the coefficient of friction and wear during tribological sliding. The results of regression and ANN models are compared in Table 3. The results obtained from these models are found close to the experimental results. So, the proposed models can be used to predict the coefficient of friction and wear during tribological sliding operation. Nonetheless, as shown in Table 3, ANN produces better results as compared to regression. Further, it should be also noted that the ANN model is very good at the training stage but not as good at the test data. However, the accuracy can be enhanced by doing more experiments and providing more tests for training the program.

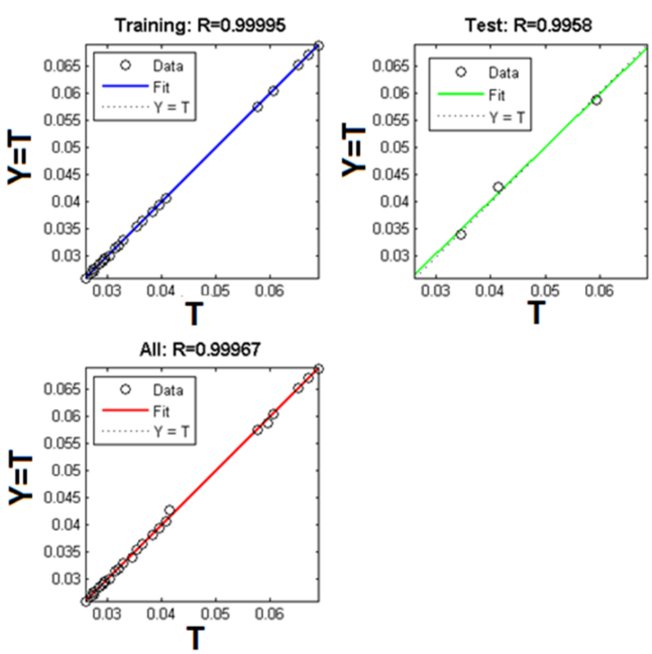

Figure 7: ANN model output for C.O.F representing training, test and combined data.

Table 3: Comparison of regression and ANN models.

	Mean Square Error (MSE)		Mean Absolute Percentage Error (MAPE)		Coefficient of Determination (R^2)	
	C.O.F	Wear	C.O.F	Wear	C.O.F	Wear
First-order regression	1.021	1.326	14.79	15.72	0.81	0.73
Second-order regression	0.016552	0.029441	7.441	7.728	0.97701	0.96932
ANN	0.001681	0.002510	2.521	2.633	0.992261	0.995575

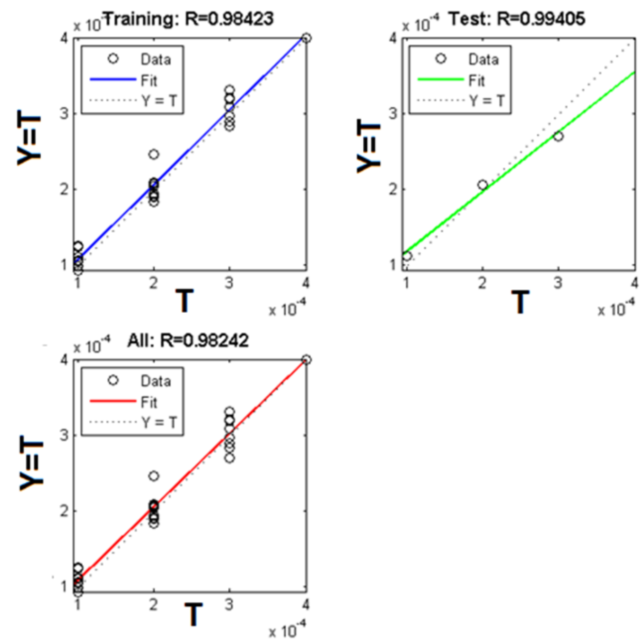

Figure 8: ANN model output for wear (weight loss) representing training, test and combined data.

4.0 CONCLUSION

In this paper, the multi-linear regression and ANN-based models were developed for the estimation and prediction of the coefficient of friction and wear during tribological sliding process. Two regression models were developed and based on the statistical parameters of mean squared error and coefficient of determination; it was observed that the second-order model yields the best estimation and prediction results than the first order. Furthermore, it was also observed that the ANN-based model gives more accurate results than the multi-linear regression models. Also, the advantages of ANN such as simplicity, speed, and capacity of learning as compared to regression, make it a powerful tool for predicting the coefficient of friction and wear during tribological sliding.

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