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Prediction the dynamic viscosity of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant using Principal Component Analysis (PCA) with Artificial Neural Network (ANN)

Mohammad Hemmat Esfe [a], Mehdi Hajian [b], Davood Toghraie [c], Mohamad Khaje khabaz [d], Alireza Rahmanian [e], Mostafa Pirmoradian [c], Hossein Rostamian [f]

[a] Nanofluid advance research team, Tehran, Iran
[b] PhD Graduate from Department of Mechanical Engineering, Isfahan University of Technology, Isfahan 84156-83111, Iran
[c] Department of Mechanical Engineering, Khomeinishahr Branch, Islamic Azad University, Khomeinishahr, Iran
[d] Young Researchers and Elite Club, Khomeinishahr Branch, Islamic Azad University, Khomeinishahr, Iran
[e] Department of Biosystems Engineering, College of Agriculture, Isfahan University of Technology, Isfahan 84156-83111, Iran
[f] University of Applied Science and Technology, Center of Chloran Chemical Production Company, Semnan, Iran

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ABSTRACT

In this study, the prediction of dynamic viscosity (μ_{nf}) of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant using Artificial Neural Network (ANN) is performed. The objective of the present research is to investigate the effect of temperature and solid volume fraction (SVF) to predict the shear rates (SR) and μ_{nf} using ANN. The feed-forward ANN consists of a multilayer perceptron network (MLP), which is capable of predicting μ_{nf} in connection with experimental data of temperature, SR and SVF. Sensitivity analysis is used to evaluate the importance and role of temperature, SR, and SVF in experimental μ_{nf} variations. ANN is generated and tested with experimental data sets and the results show that there was a good agreement between the actual and predicted ANN values. Moreover, the results of ANN simulation are compared with other data processing methods such as Support Vector Machine (SVM), Partial Least Squares (PLS), Principal Component Regression. In addition, the results of the residual value of ANN with seven neurons for μ_{nf} can be very small and close to the expected normal value. From this, it can be concluded that the given model can expect exact values.

1. Introduction

Nowadays, the use of nanotechnology in almost all branches of science is being seriously pursued [1,2]. In addition, the use of intelligent systems for predicting data, along with nanotechnology, has helped researchers in the growth and development of various branches of science [3–13]. Therefore, it seems that different branches of science in the fields of chemistry, physics, mechanics, etc. can experience many advances with nanotechnology [14–20]. The development of the lubricant industry is an important part of the improvement of the machine industry and other related industries. Statistical data show that with a small increase in the cost of producing and choosing a better lubricant, many additional and undesirable costs can be reduced. This is due to the important and beneficial effects of using lubricants, which can reduce the amount of friction between parts with a relative motion by separating them with a film of oil, and cooling the engine and its internal components, thereby reducing thermal stresses and longer life. Lubricants also seal the contact parts to prevent the diffusion of gases and fluids containing particles and carry particles due to wearing down of engine components between moving parts and collect them in the filter wall. In recent years, with the advancement of technology, the use of nanomaterials in different fields of engineering and various industries has been considered by researchers. These include the dispersion of nanoparticles in a base fluid leading to the formation of a nanofluid, first proposed by Choi

E-mail address: Toghraee@iaukhsh.ac.ir (D. Toghraie)
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and Eastman. This led to the development of lubricants with higher efficiency than conventional ones in cooling by changing some thermal properties and hydrodynamic characteristics of the base fluid [21–24]. Studies in this field show that the k_{nf} is a function of factors such as the shape, size and properties of the nanoparticles, temperature, base fluid properties, and solid volume fraction (SVF). The μ_{nf} of a lubricant is one of the most important and basic properties of the fluid which affects the flow rate and pumping power of the fluid. The investigations on μ_{nf} show their dependency on factors like temperature, particle size, SVF, nanoparticle type and base fluid [25]. μ_{nf} analysis is one of the most important key factors in determining the hydrodynamic behavior of nanofluids due to its influence on Rayleigh and Reynolds number values. Therefore, extensive studies were conducted on the effect of nanoparticles on μ_{nf}, some of which are given as follows. Kole and Dey [26] dispersed alumina nanoparticles in-car coolant and analyzed their experimental results on μ_{nf}. It was reported that SVF would increase the μ_{nf} while an increase in temperature would decrease it. Sundar et al. [27] investigated the μ_{nf} and thermal conductivity (k_{nf}) of magnetic Fe_3O_4/water nanofluid experimentally and theoretically. Hemmat Esfe et al. [28] also studied on predicting the rheological behavior of MWCNT–Al_2O_3 (30–70%)/oil SAE40 hybrid nanofluid [28]. The other study on Experimental evaluation of MWCNT–Al_2O_3 (40–60%)/5W50 hybrid nanofluid and comparison with MWCNT–Al_2O_3 (35–65%)/5W50 hybrid nanofluid with focus on thermophysical properties and cost performance index were reported by Hemmat Esfe and Alidoust [29]. Data analysis and modeling with ANN were reported by Esfe et al. [30] and in case of modeling the thermal conductivity ratio of an antifreeze-based hybrid nanofluid containing graphene oxide and copper oxide for using in thermal systems studied by Rostami et al. [31]. An experimental study on the thermal conductivity of new antifreeze containing copper oxide and graphene oxide nano-additives were reported by Rostami et al. [32]. Rostami et al. [33] also studied on The effect of hybrid nano-additive consists of graphene oxide and copper oxide on rheological behavior of a mixture of water and ethylene glycol. Using the chemical precipitation method, they prepared the nanofluid by synthesizing Fe_3O_4 nanoparticles and then dispersing them in water. A range of 0.0% to 2.0% for SVF and a variation of 20–60 °C for the temperature were considered. Their results show that increasing the SVF would increase the μ_{nf} and k_{nf} while the amount of μ_{nf} enhancement was greater than that of k_{nf}. In addition, they proposed analytical equations without resorting to Maxwell and Einstein models to predict the μ_{nf} and k_{nf}. In another study, Naina et al. [34] examined the k_{nf} of TiO_2/Water nanofluid over a range of 0.5–2.5% for SVF and temperature varying from T = 10 to 40 °C. They reported a maximum of 50% increase in μ_{nf} for 2.5 % TiO_2-water nanofluid. Murshed et al. [35] presented a combined theoretical and experimental investigation on μ_{nf} and k_{nf}. They found higher values for these parameters of the nanofluid in comparison with the base fluids. It was reported that increasing the SVF would increase μ_{nf} and k_{nf}. Moreover, they denoted that the temperature would strongly influence k_{nf}. Aladag et al. [36] examined the dependency of μ_{nf} of CNT/water and Al_2O_3/water nanofluids on the temperature and shear rates (SR) at low temperatures and SVFs. Depending on SR, the nanofluid suspensions display Newtonian or non-Newtonian behaviors. Hojjat et al. [37] studied three types of non-Newtonian nanofluids and measured their rheological characteristics with different SVFs at various temperatures. The dependency of the rheological properties of the nanofluids on the SVF and temperature was reported. Also, their results show that all nanofluids display pseudo-plastic behavior. Recently, researchers have paid attention to a new class of nanofluids containing a combination of different nanoparticles, called hybrid nanofluids, and studied their thermophysical properties. Esfe et al. [38] investigated the effect of SVF on μ_{nf} and k_{nf} of Ag–MgO/water nanofluid through an experimental study. In another study, Esfe et al. [39] measured k_{nf} of SWCNT-MgO/EG nanofluids which were produced at SVF = 0.05% to 2%. The range of temperature was considered from 30 to 50 °C through the tests. A comparison between the results of the hybrid nanofluid and nanofluids made with a single particle of MgO and SWCNT was performed. Through an experimental study, Rejvani et al. [40] examined the behavior of MWCNTs–SiO_2 (30–70)/10W40 nanofluid. The μ_{nf} was measured at SVF = 0.05 to 1% with T = 5 to 55 °C. It was reported that the behavior of the samples was so close to the pseudo-plastic Ostwald de Waele non-Newtonian model. Batmunkh et al. [41] reported a development in the k_{nf} of TiO_2 -nanofluids by adding negligible amounts of "Ag" nanoparticles. The temperature variation was considered 15–40 °C through the experiments. Suresh et al. [42] prepared a stable hybrid nanofluid in SVF = 0.1% by dispersing hybrid nanopowder Al_2O_3–Cu in deionized water. Their results show an enhancement of 13.56% in Nusselt number in comparison with that of water. Esfe et al. [43] evaluated the μ_{nf} of Al_2O_3-MWCNT (65:35)/5W50 nanofluid. The mean diameter of Al_2O_3 nanoparticles was 50 nm, and the range of inner and outer diameters of MWCNTs was 3–5 nm and 5–1 nm, respectively. The variation of temperature was between 5 and 55 °C. It was reported that the hybrid nano-lubricant behaves as a non-Newtonian fluid and increasing the SVF magnifies the non-Newtonian behavior; on the contrary while, the temperature increase had a reverse result. Chen et al. [44] investigated k_{nf} of Fe_2O_3-MWNT /Water hybrid nanofluid. Madhesh et al. [45] performed an experimental study to investigate the heat transfer and rheological properties of Cu–titania hybrid nanofluids. Although the experimental studies and the simulations performed based on molecular dynamics to determine the properties of nanofluids have provided useful and efficient results, nevertheless, their high cost and time consumption can be mentioned as disadvantages of these methods. On the other hand, when it is difficult to provide a mathematical model for a physical system, or detailed information is not available, or the process has time-dependent or nonlinear variables, the results of analytical modeling using scientific and knowledge-based methods may not be convincing. For such complex systems, simplifying assumptions may limit the accuracy of the proposed models. In addition, most of the equations used in modeling analyses cannot be applied to a wide range of processes under different conditions, because they are only suitable for a given set of conditions and can be used under certain assumptions. These ambiguities have led to a strong tendency to present methods based on the direct use of experimental data to predict process results. Examples include ANNs (Artificial Neural Networks), genetic algorithms, adaptive neural-fuzzy inference systems, and fuzzy logic, which were also used to analyze the behavior of nanofluids. Using an ANN, Toghraie et al. [46] inspected μ_{nf} of Ag/Ethylene glycol nanofluid with SVF = 0.2–2% for T = 25–55 °C. Their results show that ANN could guess the μ_{nf} with good accuracy compared to the correlation method. Esfe et al. [10] applied the ANN to predict Nusselt number and pressure drop of aqueous nanofluids. They examined the influence of different variables on pressure drop and Nusselt number. It was shown that the ANN modeling could accurately model the experimental data. Toghraie et al. [47] applied ANN to investigate the μ_{nf} of MWCNTs–ZnO/water–EG (80:20). After preparing the required experimental data, the ANN was chosen based on different generating architectures. Also, μ_{nf} was predicted by the correlation method. It was reported that the ANN was better than the correlation method in forecasting the μ_{nf}. Via ANN and RSM, Esfe et al. [48] modeled the k_{nf} of the water–titania nanofluid versus SVF and temperature. It was reported that the influence of temperature on k_{nf} was more evident than the effect of SVF. Beigzadeh [49] presented an ANFIS model to predict the μ_{nf} of Cu/Water-Glycerin

Table 1
The experimental dataset of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant [59].

T (°C)	SR value									
	50	100	200	300	400	500	600	700	800	900
	SVF = 0.05%									
5	525	491	452.8	428.1						
15		285	265.3	253.1	243.3	235.9				
25			164.1	164.1	164.1	164.1	164.1			
30										
35			105	101.3	98	96	93.8			
40										
45				68.1	66.1	64.9	63.1	62.1		
50										
55						46.5	43.4	42.3	42.9	40.8
T (°C)	SR value									
	50	100	200	300	400	500	600	700	800	900
	SVF = 0.0625%									
5		497	477.2	461.2						
15		358	345	335.6						
25										
30					327.7	321.4				
35		272	261.6	255.6	250.3	246				
40		203	196.9	193.1	189.8	186				
45			150.9	148.1	145.3	143.6	141.3			
50			117.2	114.4	113	111	109.7			
55										
T (°C)	SR value									
	50	100	200	300	400	500	600	700	800	900
	SVF = 0.1%									
5	566	531	485.6	460.6						
15		306	285.9	271.9	260.6	252.4				
25			175.3	168.8	162.7	158.2	154.1			
30										
35			112.5	108.1	105.5	103.1	100.9			
40										
45				73.1	71.3	70.1	67.8	67		
50										
55					48.8	49.1	46.9	46.1	46.2	
T (°C)	SR value									
	50	100	200	300	400	500	600	700	800	900
	SVF = 0.25%									
5	596	561	519.4	494.4						
15		324	302.8	287.5	276.6	267.8				
25		197	185.6	178.1	172.5	167.6				
30										
35			118.1	115	112	109.9	106.6			
40										
45				80	75.9	74.3	72.8	71.3		
50										
55					53.9	52.5	50.3	49.8	49	
T (°C)	SR value									
	50	100	200	300	400	500	600	700	800	900
	SVF = 0.5%									
5	626	587	540.9	514.4						
15		339	317.8	303.1	291.6	281.6				
25		208	195	186.9	180	175.1				
30										
35			124.7	120.6	117.2	114.4	111.9			
40										
45				81.3	79.2	77.6	75.6	74.7		
50										
55					54.8	54.4	53.1	52	51.8	
T (°C)	SR value									
	50	100	200	300	400	500	600	700	800	900
	SVF = 0.75%									
5	664	619	568.1	542.5						
15		358	331.9	316.2	304.7	295.5				
25		216	202.5	194.4	188	183				
30										
35			130.3	125.6	121.9	118.9	116.6			
40										
45				85.6	83	81.4	80	78.2		
50										
55					58.6	57	55	54.4	53.7	
T (°C)	SR value									
	50	100	200	300	400	500	600	700	800	900
	SVF = 1%									

(continued on next page)

Table 1 (*continued*)

T (°C)	SR value									
	50	100	200	300	400	500	600	700	800	900
	SVF = 0.05%									
5	525	491	452.8	428.1						
5	720	671	618.8	587.5						
15		384	358.1	341.9	329.5	318.8				
25		233	217.5	209.4	202.5	197.3				
30										
35			140.6	135	131.7	128.6	125.9			
40										
45			94.7	91.3	88.1	86.3	84.4			
50										
55				64.4	61.4	60.4	58.7	57.9		

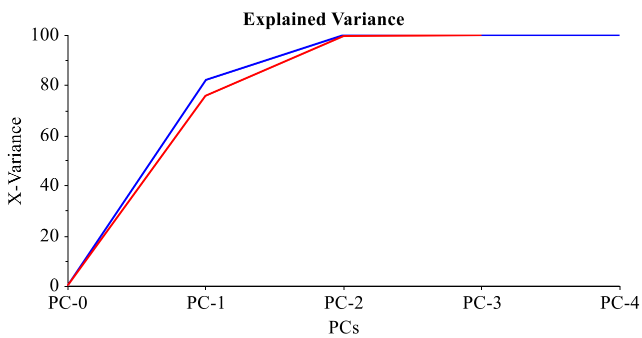


Fig. 1. Determination of Principal Component Analysis (PCA) for overall data.

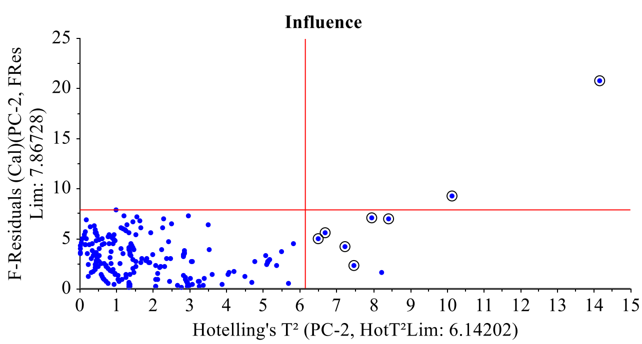


Fig. 2. Detection of outliers using PCA method.

nanofluid. Appropriate matching of ANFIS estimating results with the test data set show the reliability of their model. By utilizing ANN, Esfe et al. [8] examined the impact of different temperatures SVFs on μ_{nf} of MWCNT–Al_2O_3 (30–70%)/Oil SAE40 nanofluid. Some experiments were performed to obtain the required data to train an ANN. The results of well-trained ANN show that when SVF increases, the μ_{nf} would increase at all temperatures while increasing the temperature resulted in decreasing the μ_{nf}.

In this study, the prediction of μ_{nf} of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant using ANN was performed. The objective of the present research is to investigate the effect of temperature and SVF to predict the SRs and μ_{nf} using ANN. The feed-forward ANN consists of a MLP, which is capable of predicting μ_{nf} in connection with experimental data of temperature, SR and SVF.

2. Material and methods

ANNs are numerical and mathematical models composed by a few neurons organized completely different layers, connected through the variable weights. These weights are calculated by an iterative strategy among the training process when a large amount of training data representing, the pattern to be modeled, input and output pairs are supplied to the network [50]. In the ANN analysis, multi-layer ANNs with back propagation (BP) learning algorithm were used to predict μ_{nf} of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant. Data used in this work is taken from literature [59]. Back propagation is an ANN algorithm which, performed learning on a multilayer feed-forward ANN [46]. In order to achieve the outputs a large number of inter-connected processors called neurons organized in layers. A three-layer (input, hidden and output) ANN with a large number of nodes in each layer connected the knowledge of inputs with outputs. The strength (weights) of connections are achieved through a learning process. The main objective is to study the variation of μ_{nf} within a certain range of temperature, SR and SVF of hybrid nano-lubricant to find critical values of variation in the behavior of hybrid nano-lubricants for each of the parameters. In other words, in the present study, the ANN is trained by using temperature, SVF, and SR experimental data to estimate the μ_{nf} of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant. In order to simulate the ANN model, a real dataset collected from experiment have been used. Table 1 contains some information from MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant.

Initial data is typically split into 70% for training, 10% for validation, and 20% for testing the efficiency of the model. Validation data prevent ANN overtraining due to premature outages and generalize ANN results.

3. Results and discussion

In the present study, experimental data, including temperature, SR, and SVF, are first obtained and compared to μ_{nf} data through Principal Component Analysis (PCA), a discounting method. This approach is frequently utilized to calculate the measurements of large-scale data. A unit that includes an expansive set of parameters, gets to be a small set of parameters that contains the greatest value of total data. Fig. 1 shows the results of PCA for overall data. As shown in Fig. 1, the second principal component was utilized as an index of the variation of all data and different measurable characteristics. This indicator is usually utilized to recognize outliers. Since the PCA minimizes the quadratic norm, it either has the same least-squares issue or is delicate to exceptions in a Gaussian conveyance. By squaring, deviations from exceptions overwhelm the common criteria and, as a result, can drive PCA components. Outliers were analyzed utilizing the PCA strategy and expelled from the general data, as illustrated in Fig. 2 [51,52]. Due to the PCA minimizing quadratic norms, it has the same least-squares problems, or it becomes Gaussian the sensitivity to outliers. By squaring, deviations from outliers, can dominate the general norm and consequently drive PCA components.

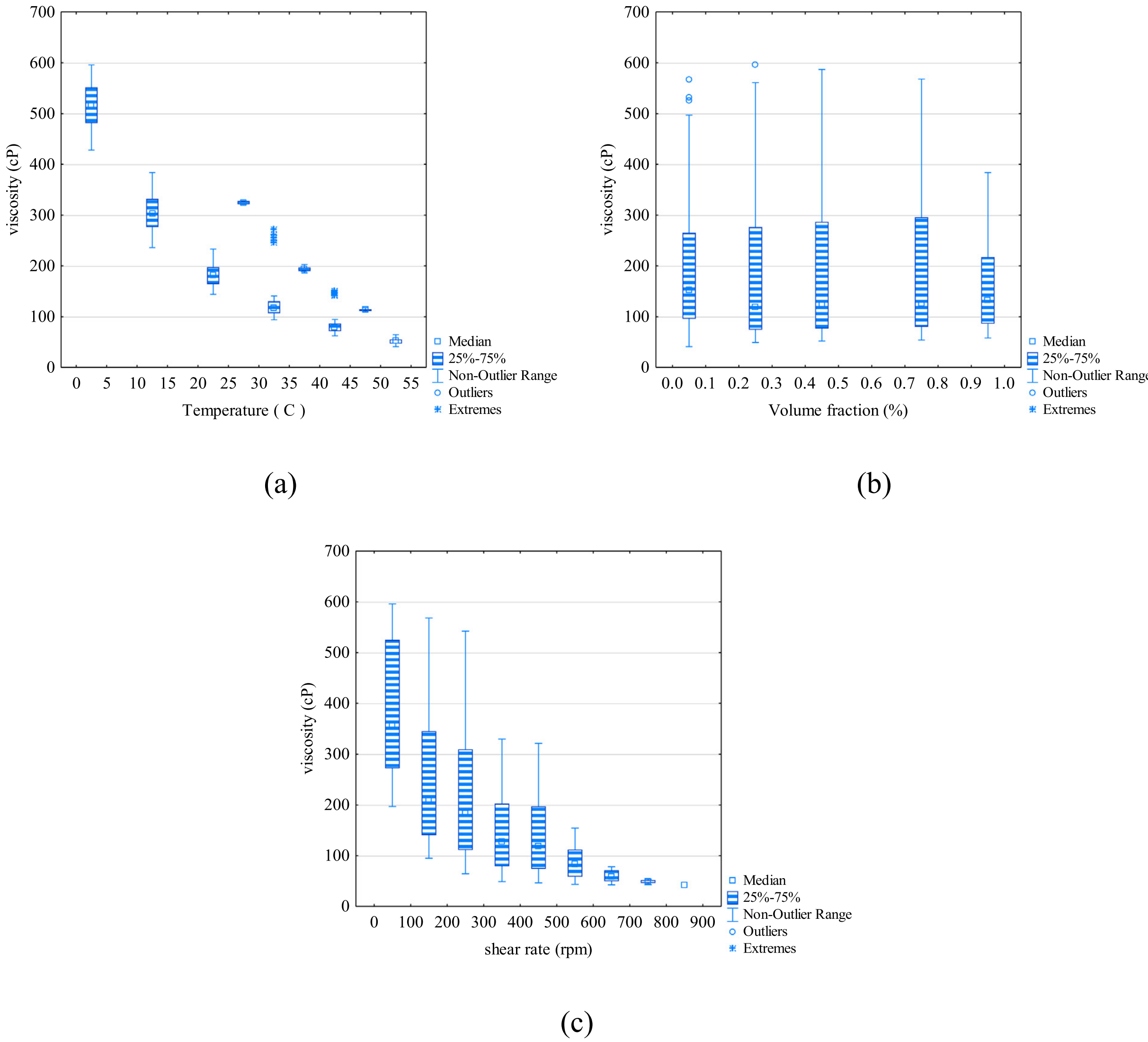


Fig. 3. Dispersion of μ_{nf} values against (a) temperatures, (b) SVF and (c) SR.

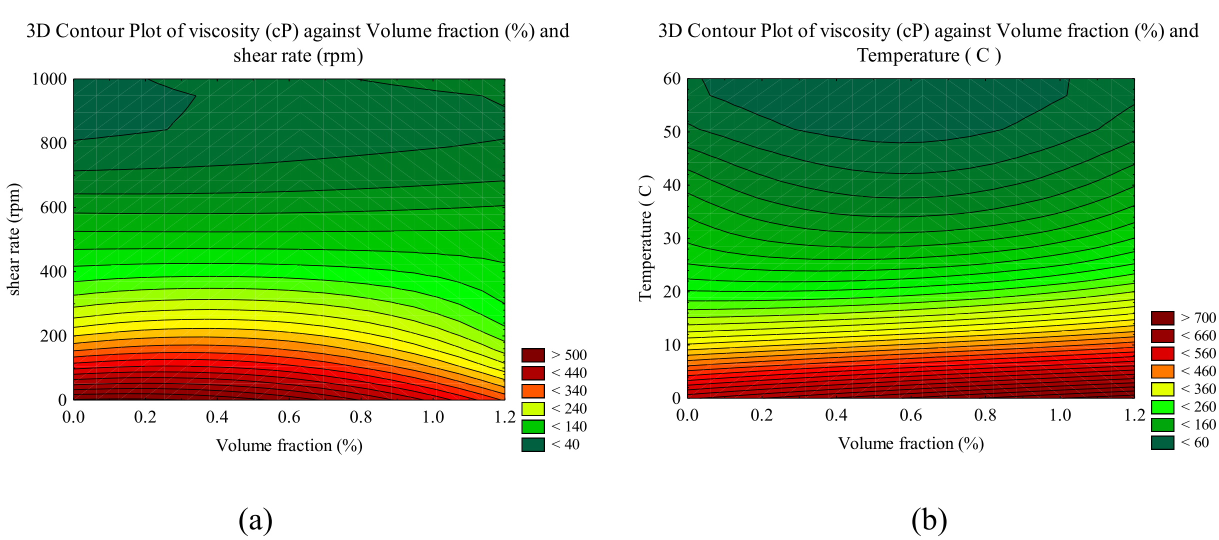


Fig. 4. Effect of SVF changes on μ_{nf} of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant in the presence of: (a) SR and (b) temperature.

Table 2
The comparison of the prepared values for error and correlation rate of different simulated networks.

No.	ANNs	Training perf.	Test perf.	Validation perf.	Train error	Test error	Validation error
1	MLP 3-5-1	9.78E-01	9.78E-01	8.99E-01	4.78E-02	3.59E-02	8.44E-02
2	MLP 3-10-1	9.79E-01	9.79E-01	9.02E-01	4.60E-02	3.40E-02	8.38E-02
3	MLP 3-9-1	9.74E-01	9.76E-01	8.97E-01	5.64E-02	3.82E-02	8.57E-02
4	MLP 3-10-1	9.76E-01	9.75E-01	9.04E-01	5.38E-02	4.03E-02	8.05E-02
5	MLP 3-4-1	9.49E-01	9.56E-01	8.94E-01	1.13E-03	7.46E-02	9.89E-02
6	MLP 3-7-1	9.76E-01	9.75E-01	8.98E-01	5.30E-02	4.12E-02	8.46E-02
7	MLP 3-5-1	9.73E-01	9.73E-01	9.00E-01	5.99E-02	4.29E-02	8.26E-02
8	MLP 3-4-1	9.69E-01	9.69E-01	8.99E-01	6.68E-02	4.92E-02	8.40E-02
9	MLP 3-9-1	9.77E-01	9.77E-01	8.97E-01	4.97E-02	3.78E-02	8.56E-02
10	MLP 3-3-1	9.76E-01	9.75E-01	8.98E-01	5.25E-02	4.13E-02	8.50E-02
11	MLP 3-8-1	9.75E-01	9.75E-01	9.02E-01	5.61E-02	4.09E-02	8.15E-02
12	MLP 3-10-1	9.50E-01	9.56E-01	8.94E-01	1.13E-03	7.53E-02	1.00E-03
13	MLP 3-3-1	9.49E-01	9.56E-01	8.96E-01	1.13E-03	7.54E-02	9.85E-02
14	MLP 3-9-1	9.77E-01	9.78E-01	8.93E-01	4.98E-02	3.66E-02	9.02E-02
15	MLP 3-8-1	9.74E-01	9.76E-01	8.95E-01	5.67E-02	3.98E-02	8.80E-02

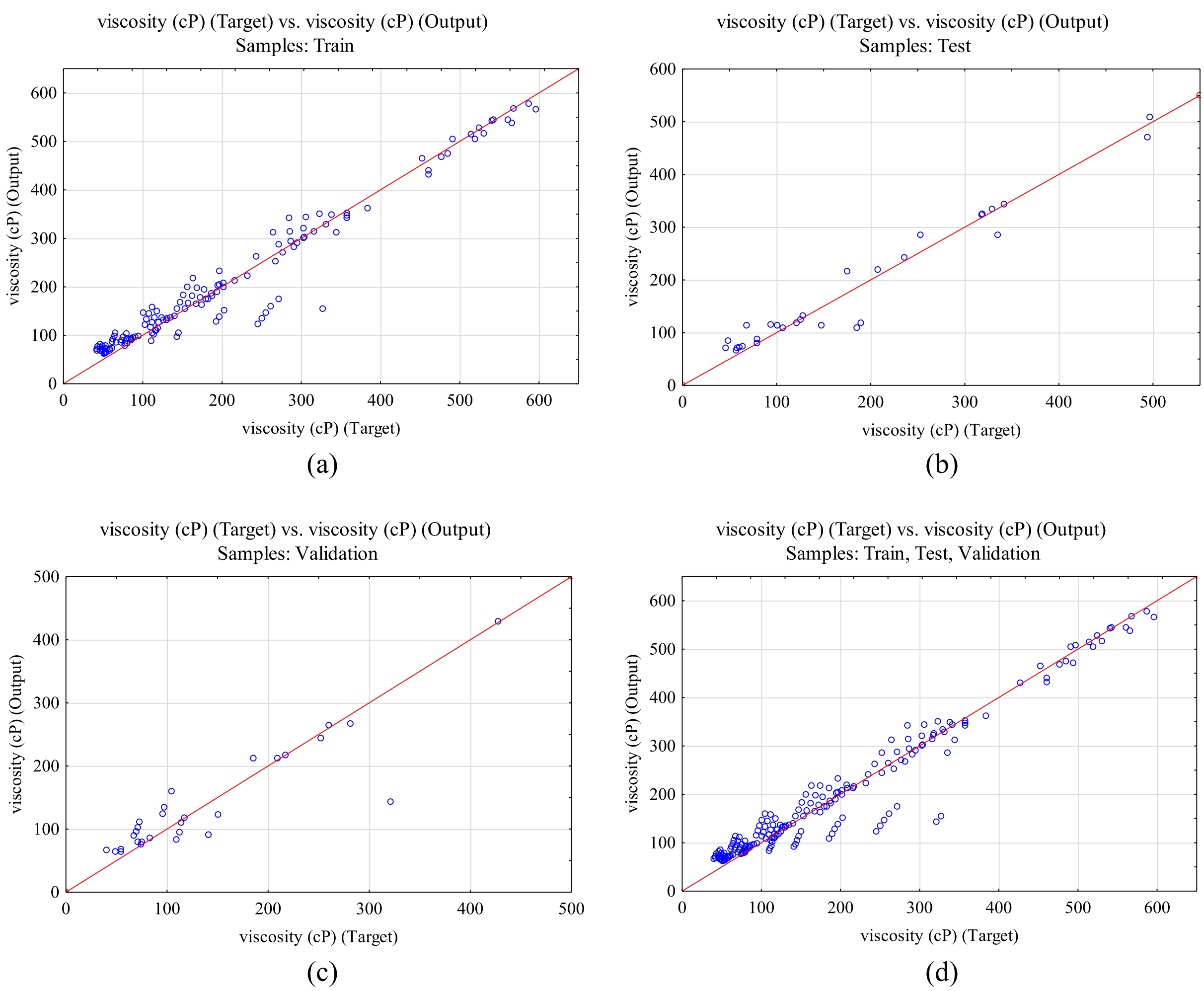


Fig. 5. Correlation diagram between predicted and experimental μ_{nf} from: (a) train, (b) test, (c) validation, and (d) all data.

The deviation of μ_{nf} of the MWCNT-Al_2O_3 (30:70)/Oil 5W50 hybrid nano-lubricant and its range are depicted in Fig. 3 based on different temperatures, versus various SVF and SR.

The effects of volume fraction variations versus the different shear rates and temperature were presented in Fig. 4 for MWCNT-Al_2O_3 (30:70)/Oil 5W50 hybrid nano-lubricant. Notably, the maximum μ_{nf} values for MWCNT-Al_2O_3 (30:70)/Oil 5W50 hybrid nano-lubricant occurs at values below 5°. It can be observed that the μ_{nf} arises decreasing by SR changes from 50 to 900 rpm. Fig. 4 depicts the effect of 3D plot SVF against SR and temperature to determine their maximum and minimum values.

For training data, when the network weights are randomly chosen, the amount of MSE is exceptionally high, and significantly decreased by the training loops. To get the best performance ANN for each training calculation, 15 distinctive ANNs are trained with different layers, and the networks with the slightest error and highest performance are chosen to predict the problem. Table 2

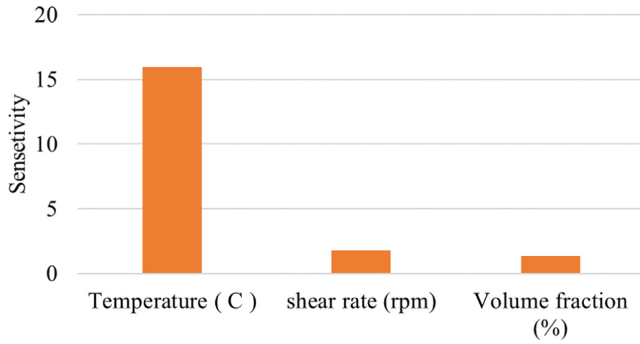


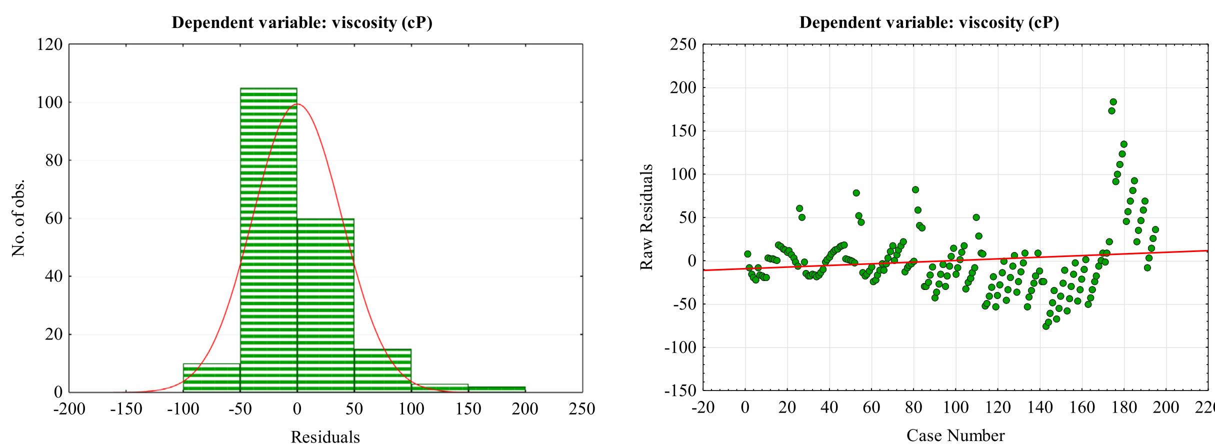
Fig. 6. The sensitivity analysis of ANN model.

lists the comparison of the prepared values for error and correlation rate of different simulated ANNs.

The performance results and regression diagram are indicators to ensure proper ANN training, which presented the variations in Mean Square Error (MSE) in terms of training stages. Simulation No. 11 (MLP 3-8-1) in Table 2, selected as a best-trained ANN. The simulated ANNs shown in Fig. 5, where the great performance and the lowest error, among the validation data, test and training data μ_{nf} of MWCNT-Al2O3 (30:70)/ Oil 5W50 hybrid nano-lubricant and experimental data can be observed. The regression figures illustrate the dependence of the experimental output on the predicted values. The correlation performance μ_{nf} of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant model predicts the outputs with training, test and validation values of 0.97, 0.97 and 0.90, respectively. The ANN models developed in the present study can be successfully utilized to provide an accurate prediction of the properties.

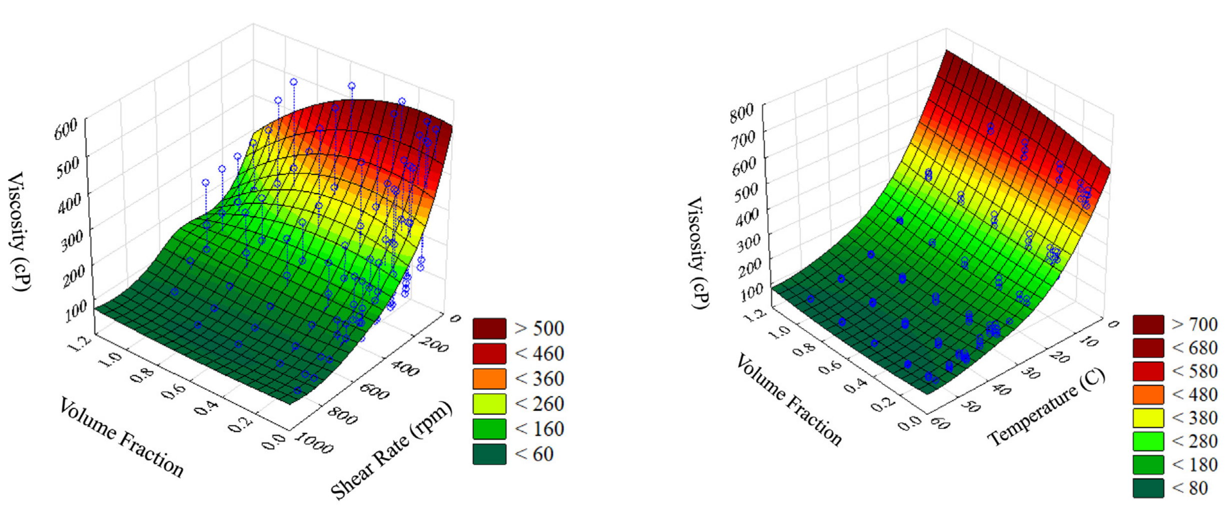
Fig. 6 depicts the sensitivity analysis of the ANN model that was achieved from the temperature, SR and SVF parameters. As shown, the most sensitivity values were obtained for temperature, which concluded that these characteristics had the most levels of significance to predict the results [50]. It guarantees the effectiveness of the ANN method.

Fig. 8 show the three-dimensional surf for μ_{nf} of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant output. It can be obtained



(a) (b)

Fig. 7. .The error graphs depicted different error aspects of MLP 3-8-1 in way of histogram of residuals (a), raw residual of case numbers (b).



(a) (b)

Fig. 8. Three-dimensional surf for μ_{nf} of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant against (a) SVF and SR and (b) SVF and temperature.

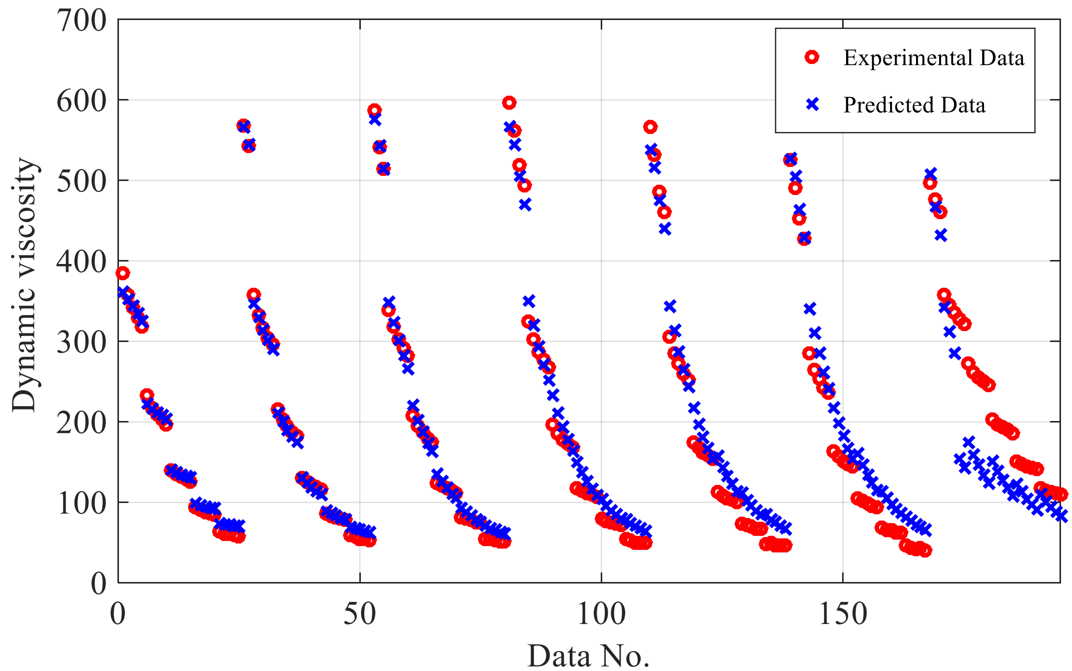


Fig. 9. Comparing the experimental data and ANN data.

from the figures that the excellent agreement of ANN as an approximation function of the μ_{nf} is achieved. It can be concluded that the temperature has a significant effect on μ_{nf}. In addition, with increasing the SVF of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant the effect of shear rate increases, enhancing the μ_{nf}.

Fig. 9 illustrates the μ_{nf} of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant compared to the experimental data and the simulated ANN output. From this, we can conclude that the experimental data are close to the simulated ANN and accurately predict the results. The ANN was generated and tested using the collected experimental datasets and the results show that there was a good match between the actual and predicted values of the ANN.

Table 3 shows the results of data processing by various methods. These methods include support vector machines (SVM), partial least squares (PLS) method, and PCR. The SVM was presented by Vapnik [53,54]. The distinctive features of SVM and ability to promise empirical performance, causing to utilize them for the facial expression classification problem. SVM is a supervised machine learning algorithm that can be used for classification and regression purposes. Support vector machines can also be used as a regression method, preserving all the key features (maximum margins) that characterize the algorithm. You can use SVM to determine the acceptable error in your model and find a line (or higher dimensional hyperplane) that fits your data. In this case, the polynomial algorithm and its parameters were used: ν = 0.5, γ = 0.3333333. Partial least squares regression (PLS) regression is a fast, efficient, and optimal covariance-based regression method that is recommended for regressions with many explanatory variables [55,56]. The explanatory variables tend to correlate. PLS is a transformer or regressor and is in many ways similar to PCR. It also shrinks the sample before using the linear regressor on the transformed data. The main difference from PCR is that PLS Transformation is monitored [50,57].

Multiple Linear Regression (MLR), also known as multiple regression, is a statistical technique that uses several independent variables to predict the outcome of a response variable. MLR is an extension of Linear Regression (LS) that uses only one independent variable. As can be seen from Table 3, the best training methods related to the Broydon - Fletcher - Goldfarb - Shann (BFGS) algorithm is due to having the least amount of error and highest performance. The ANN during the other method led to the selection, which we will explain and analyze in the following Regression and Performance diagrams.

Fig. 7 presents error graphs for various aspects of the MLP 3-8-1 error such as the difference between the residual and the expected normal. In Fig. 7, the error values demonstrate that ANN is working appropriately, which the training approach is satisfactory. Therefore, the expected dynamic viscosity results of MLP 3-8-1 are very good predictors. In addition, the resulting ANN residuals of 8 neurons at dynamic viscosity were very low and probably close to the expected normal. From this, we can conclude that a given model can be expected to have exact values.

Here, a BFGS 30 algorithm of an ANN with a single hidden layer and 8 neurons is used to effectively estimate the μ_{nf} [58]. Given the obtained ANN structure, the μ_{nf} of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant can be expressed as follows:

Prediction equation for:

Dynamic viscosity (cP) = 617.632880923–0.292162141822×"shear rate (rpm)"+3.7711289518e-005*"shear rate (rpm)"^{2}-18.0033836373×"Temperature (C)"+0.179362244142×"Temperature (C)"^{2}-25.7678671818×"Volume fraction (%)"+68.2130447442×"Volume fraction (%)"^{2} + 0.00249886204997×"shear rate

Table 3
The results of the error and coefficient correlation rate of method.

	Performance	Algorithm	Function
MLP 3-8-1	0.974831531	BFGS 30	Logistic, Exponential
SVR (Support Vector Machine)	0.9257911	Polynomial	ν = 0.5, γ = 0.3333333
PLS (Partial Least Squares)	0.8090009	NIPALS	full Cross validation
PCR (Principal Component Regression)	0.8090013	NIPALS	full Cross validation
MLR (Multiple Linear Regression)	0.8060046	–	Leverage correction

(rpm) × Temperature (C)"+0.145307636612×"shear rate (rpm) × Volume fraction (%)"-2.91427313409×"Temperature (C) × Volume fraction (%)"(1).

4. Conclusion

In this study, the prediction of μ_{nf} of MWCNT-Al_2O_3 (30:70)/ Oil 5W50 hybrid nano-lubricant using ANN was performed. The feed-forward ANN consists of an MLP, which is capable of predicting μ_{nf} in connection with experimental data of temperature, SR and SVF. The following results were obtained:

- ANN was generated and tested with experimental data sets and the results show that there was a good agreement between the actual and predicted ANN values.
- The results of the residual value of ANN with eight neurons for μ_{nf} can be very small and close to the expected normal value.
- Using ANN BFGS algorithm, lead to 5.6e-02 in MSE and 97% as a correlation coefficient for predicting μnf.
- Error diagrams demonstrated the suitability of ANNs as tools for determining the function of μnf and the learning algorithm used.
- The results of ANN simulation are compared with other data processing methods such as SVM, PLS, Principal Component Regression.
- In some cases, the trend of the targets is simply adjusted by a linear function called identity in the output layer.

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