https://doi.org/10.3311/PPch.37179

Periodica Polytechnica Chemical Engineering, 68(4), pp. 571–581, 2024

Predicting Dynamic Viscosity in Nanofluids of Graphene Nanoplatelets and SAE10W Oil Utilizing Artificial Neural Networks

Sekar Manikandan[1], Adhinarayanapuram Jayaram Devanathan Nanthakumar[1*]

[1] Vehicle Dynamics Laboratory, Department of Automobile Engineering, College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur Campus, 603203 Chengalpattu, Tamilnadu, India
[*] Corresponding author, e-mail: nanthakd@srmist.edu.in

Received: 23 April 2024, Accepted: 21 August 2024, Published online: 10 October 2024

Abstract

Viscosity is an essential factor when selecting nanofluids, as it significantly impacts their thermal behavior and heat transfer characteristics. This study aims to develop a prediction model for the dynamic viscosity of damper oil (Grade: SAE10W) nanofluid containing graphene nanoplatelets (GnPs) using an artificial neural network (ANN) based on experimental data. With high precision, ANN accurately predicts the dynamic viscosity variations with nanoparticle volume concentration and temperature. The use of a network with one hidden layer and 10 neurons resulted in a regression coefficient of 0.9998, indicating high accuracy with a simple structure. Furthermore, a mathematical correlation derived using the curve fitting method resulted in a coefficient of determination value of 0.9990. These models were evaluated in terms of percentage error to determine their accuracy. The error range for the ANN model was between −0.89% and 0.66%, and for the mathematical correlation, it was between −6.74% and 5.27%. In comparison to the mathematical correlation, the ANN model predicts better the dynamic viscosity of GnPs-SAE10W oil nanofluids. Hence, this model has the potential in the development of applications related to heat transfer.

Keywords

dynamic viscosity, nanofluid, graphene nanoplatelets, artificial neural networks, mathematical model

1 Introduction

Heat transfer equipments are widely used in a variety of industrial and engineering applications. To enhance the efficiency of a heat transfer equipment, modifications are often necessary. Modifications can include changing the size of the equipment or improving the properties of the heat transfer fluids. Such modifications are essential for optimizing the heat transfer process, which in turn can lead to significant improvements in the overall performance of the thermal systems. Also, the development of material science and technology is always introducing new concepts in the construction and working of heat transfer equipment. Such constant advancement makes it possible for modern heat transfer systems to be more efficient, dependable, and capable of meeting the increasing needs of the various sectors. To meet industry demands for energy efficiency and sustainability, continuous improvement in heat transfer equipment is necessary [1–3]. Minimalizing heat transfer equipment has its drawbacks, such as less space for installation and maintenance, higher prices, and smaller dimensions [4]. Hence, a detailed investigation of heat transfer fluids is necessary for cooling and heating to improve the energy efficiency of thermal systems. The heat transfer characteristics of a fluid are greatly affected by its dynamic viscosity (μ_{nf}) and thermal conductivity, which are major contributing factors [5, 6]. A low-viscosity fluid is ideal for pumping applications. Higher thermal conductivity also helps with faster heat transfer rates. A colloidal suspension of nanoparticles (less than 100 nm) in a base fluid, also known as nanofluid, enhances these properties [7]. The last several decades have seen a wide variety of applications for nanofluids. Fig. 1 illustrates the usage of nanofluids in different sectors, such as energy, heat exchangers, heat transfer, medical, electronics, and military applications.

Choi and Eastman [8] demonstrated that the addition of nanoparticles can significantly improve the thermal conductivity of conventional fluids. Many researchers are using this method to enhance the thermophysical

Cite this article as: Manikandan, S., Nanthakumar, A. J. D. "Predicting Dynamic Viscosity in Nanofluids of Graphene Nanoplatelets and SAE10W Oil Utilizing Artificial Neural Networks", Periodica Polytechnica Chemical Engineering, 68(4), pp. 571–581, 2024. https://doi.org/10.3311/PPch.37179

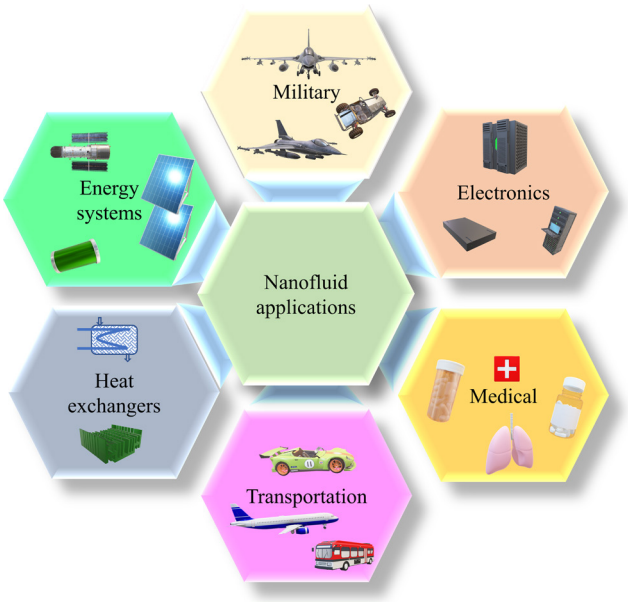

Fig. 1 Applications of nanofluids

properties of base fluids. Carbon nanotubes and metallic or non-metallic oxide nanoparticles significantly enhance the thermophysical characteristics of heat transfer fluids, according to numerous studies [9].

However, several studies have shown that the dispersion of additives in fluids affects their viscosity. Variations in temperature (T) and volume concentration (φ) can influence the viscosity of nanofluids. Moreover, researchers have devised mathematical correlations based on experimental studies to determine the thermophysical properties of nanofluids [10]. Dehghani et al. [11] conducted the experiments based on Al_2O_3 and WO_3 nanoparticles using liquid paraffin and deionized water. The authors measured the μ_{nf} by varying T and mass fractions (MFs). Also, a correlation was developed to predict the viscosity of the nanofluid with an average deviation of less than 10%. Hemmat Esfe [12] investigated the viscosity and shear stress of CuO/ethylene glycol (EG) nanofluids in a T range of 27.55 to 50 °C, and φ ranging between 0% and 1.5%.

Subsequently, a correlation was established with a 4% error compared to the experimentally measured values. In another study [13], an experimental investigation was carried out on the μ_{nf} of multiwall carbon nanotubes (MWCNT)-Al_2O_3 (40:60)/Oil 5W50 hybrid nano-lubricant, and a correlation for prediction was then developed. Nguyen et al. [14] conducted experimental investigations and developed correlations for the viscosities of Al_2O_3, CuO, and water-based nanofluids. The study explored the impact of both T and particle size on these viscosities. Aberoumand et al. [15] conducted an investigation into the viscosity and thermal conductivity of a silver nanofluid in an oil-based fluid, studying the variations as a function of nanoparticle φ. Wang et al. [16] investigated the thermophysical properties of GnPs/water nanofluids and developed a correlation to predict the viscosity accurately. They achieved a high level of accuracy with a coefficient of determination (R^2) value of 0.99. Soltani and Akbari [17] investigated the μ_{nf} of MgO-MWCNT/EG hybrid nanofluids, considering the influence of T and φ. A novel correlation was developed to predict the μ_{nf} of these nanofluids. Manikandan and Nanthakumar [18] investigated and developed a mathematical model for predicting the thermophysical properties of Cu/damper oil nanofluids, with a margin of deviation (MOD) ranging from −3.7 to 7%. The summary of research studies related to the correlation developed for predicting μ_{nf} is presented in Table 1 [11, 12, 14–17].

Mathematical correlations can be derived using experimental data through fitting and regression analysis, but they are not always reliable predictors [19]. To achieve precise predictions, researchers have turned to machine learning techniques to predict the thermophysical properties of nanofluids [20–22]. An artificial neural networks (ANN) model was developed to forecast the viscosity of MWCNT-MgO/SAE40 nano lubricants from experimental datasets. The ANN model exhibits a regression coefficient (R) of 0.9999 and a mean square error of 0.00145. The MOD of the ANN model falls within the range of ±1% [23]. In another study [24], an ANN model was developed to predict the viscosity of MWCNT-CuO/Oil 10W40 nano lubricants. The ANN model has MOD for all data and test data that falls within less than 15% range.

Chu et al. [25] conducted experiments and RSM/ANN models were used to investigate the rheological behavior of hybrid nanofluids for MWCNT-TiO_2/5W40. The ANN model demonstrated superior accuracy in predictions compared to the mathematical model, with an observed maximum error below 5% and an R^2 value of 0.999. Bhat and Qayoum [26] investigated the viscosity of CuO/EG nanofluids by considering their size, φ, and T. They utilized an ANN model to forecast the effective viscosity and compared the correlation. Although the proposed correlation exhibited R^2 values of 0.95 and 0.90 for the correlation and ANN models, respectively, it was found to be less effective than ANN modeling in predicting effective viscosity. Fan et al. [27] predicted the μ_{nf} of the WO_3-MWCNT/water-EG hybrid nanofluids using ANN model. The findings reveal that a well-trained ANN is generated using the trainlm method, with a mean square error (MSE)

Table 1 The summary of research studies related to the correlation developed for predicting viscosity of nanofluids*

Authors	Nanoparticles	Base fluid	Concentration (%)	Temperature (°C)	Correlation
Dehghani et al. [11]	Al_2O_3-WO_3	Deionized water and liquid paraffin	0.1, 0.5, 1, and 5 wt%	5, 25, 45, and 65 °C	For aqueous nanofluid $\frac{\mu_{nf}}{\mu_b}=\frac{B_1\cdot\lambda^a+B_2\cdot T^b+B_3\cdot w^c+B_4}{1.5447\cdot e^{-0.023\cdot T}}$ where, $B_1=-1.228$, $B_2=-3.027$, $B_3=0.575$, $B_4=6.256$, $a=-0.206$, $b=0.130$, $c=0.192$. $\lambda=\frac{Mw_{np}\cdot\rho_{np}}{Mw_{bf}\cdot\rho_{bf}};\ \lambda\lambda'=1$ For non-aqueous nanofluid $\frac{\mu_{nf}}{\mu_b}=\frac{A_1\cdot\lambda^{\acute{a}}+A_2\cdot T^{\acute{b}}+A_3\cdot w^{\acute{c}}+A_4}{52.36\cdot e^{-0.013\cdot T}}$ where, $A_1=-32.072$, $A_2=-6.191$, $A_3=12.895$, $A_4=116.64$, $\acute{a}=0.136$, $\acute{b}=0.513$, $\acute{c}=0.346$. $\lambda'=\frac{Mw_{bf}\cdot\rho_{bf}}{Mw_{np}\cdot\rho_{np}};\ \lambda\cdot\lambda'=1$
Hemmat Esfe [12]	CuO	Ethylene glycol	0–1.5 vol%	27.5–50 °C	$\frac{\mu_{nf}}{\mu_b}=a_0+a_1\cdot\varphi+a_2\cdot\varphi^2+a_3\cdot\varphi^3+a_4\cdot\varphi^4$ where, coefficients at 30 °C, $a_0=0.9876$ $a_1=0.8065$, $a_2=3.148$, $a_3=-3.418$, $a_4=1.268$
Nguyen et al. [14]	Al_2O_3, CuO	Water	<4 vol%	27–75 °C	$\frac{\mu_{nf}}{\mu_b}=1.475-0.319\cdot\varphi+0.051\cdot\varphi^2+0.009\cdot\varphi^3$
Aberoumand et al. [15]	Ag	Oil	0.12–0.72 vol%	25–60 °C	$\frac{\mu_{nf}}{\mu_b}=1.15+1.061\cdot\varphi-0.5442\cdot\varphi^2+0.1181\cdot\varphi^3$
Wang et al. [16]	GnP	Water	1 wt%	–	$\mu=0.004\cdot(1-\mathrm{MF})^{-77.5}\cdot\exp\left(\frac{1652}{T}\right)$
Soltani and Akbari [17]	MgO-MWCNT	Ethylene glycol	0–1.0%	30 °C–60 °C	$\frac{\mu_{nf}}{\mu_b}=\left[0.191\cdot\varphi\cdot0.240\cdot\left(T^{-0.342}\cdot\varphi^{-0.473}\right)\right]\cdot\exp\left(1.45T^{0.120}\cdot\varphi^{0.158}\right)$

* μ_{nf}: Dynamic viscosity of nanofluid (Pa·s), μ_b: Dynamic viscosity of basefluid (Pa·s), λ,λ': nanoparticles and basefluid physical properties, T: Temperature (°C), w: Mass (%), Mw_{np}: Molecular weight of nanoparticle (g·mol^{-1}), Mw_{bf}: Molecular weight of basefluid (g·mol^{-1}), ρ_{np}: Density of nanopartilcle (g·cm^{-3}), φ: Volume concentration (%), MF: Mass fraction (%)

value of 0.00042 and an R^2 of 0.998 for predicting μ_{nf} of the nanofluids. Hence, numerous researchers have concluded that ANN demonstrate greater accuracy in predicting nanofluid properties. According to literature studies, the most viscosity models are available in water and EG-based nanofluids. However, only a handful of studies have focused on oil-based nanofluids and developed prediction models. Further research is needed to explore the behavior of oil-based nanofluids and to develop more accurate models for predicting their viscosity.

This research aims to develop a model that can predict the viscosity of GnPs-SAE10W oil nanofluid using ANN and a curve-fitting method. The investigation examines various neural network structures and mathematical correlations, including the incorporation of nanoparticles φ and T. Additionally, various graphs present a comparison between experimental data and modeling results. It is expected that this analysis will aid in a more comprehensive understanding of oil-based nanofluids' potential industrial applications for heat transfer process.

2 Materials and methods

2.1 Experimental data collection

In this research, investigations were carried out using graphene nanoplatelets (GnPs) incorporated into an automotive damper oil (India Yamaha Motor PVT. Ltd, grade: SAE10W). The grade 4O+ GnPs purchased from Cheap Tubes Inc (USA) are supplied in nanosheet form with a

specific surface area of 700 m^2/g, a thickness of 4 nm, and lateral dimensions of 2 µm. The GnPs dry powder is black color and 99% purity. A two-step process [28] was followed to meticulously prepare the nanofluids, with varying nanoparticle φ ranging from 0.050% to 0.150%. Accurate and systematic experimental measurements were carried out in accordance with ASTM D445-24 [29] standard, and the kinematic viscosity of the prepared nanofluids was measured utilizing a Cannon-Fenske Routine Viscometer with a precision level of ±0.2%. Measurements were made to determine the kinematic viscosity of the nanofluid at T between 20 °C to 80 °C with intervals of 10 °C. The μ_{nf} was calculated by multiplying the obtained kinematic viscosity values by the density of the nanofluid. The experimental dataset that corresponds to the μ_{nf} of GnPs/SAE10W oil nanofluids is presented in Table 2.

2.2 Modeling with ANN

The popularity of ANN has increased over the past few years because of their efficiency in modeling complex relationships and making accurate predictions [30, 31]. ANN are computational models that are inspired by the structure and function of the human brain, allowing them to learn and generalize from data [32]. There are three layers in the ANN architecture. The initial layer acts as the input layer, transmitting information to the following layer, which is referred to as the hidden layer. The third layer is responsible for producing output. The inputs to the network include φ and T (input data), while the output is the predicted μ_{nf} (target data). The neurons within all layers establish connections through weight coefficients (w_{ij}). Each neuron takes these weight coefficients, multiplies them by the corresponding input received, and aggregates them to generate the output, as depicted in Fig. 2. The processing progresses until the discrepancy between successive output datasets is minimized. This convergence can be described in Eq. (1) [33] with parameters inherent to characterizing ANN, including weights (w_{ij}), biases (b_i), and an activation function (f). The output layer receives the purelin activation function, along with the tansigmoid. The Levenberg-Marquardt (trainlm) learning algorithm is employed in the modeling process using the nntool in MATLAB.

Table 2 μ_{nf} of GnPs/SAE10W oil nanofluids (mPa·s)

T (°C)	φ (%)				
	0.05	0.075	0.1	0.125	0.15
20	47.75	47.41	47.14	46.23	45.65
30	37.89	37.46	37.07	36.56	36.20
40	30.28	29.68	29.09	28.91	28.62
50	20.98	20.59	20.22	20.15	20.01
60	12.92	12.77	12.67	12.56	12.51
70	8.79	8.55	8.32	8.26	8.15
80	4.86	4.74	4.60	4.37	4.15

$$y_j = f\left(\sum_{i=1}^{n} w_{ij}x_i + b_i\right) \tag{1}$$

Where y_i represents the output, x_i is the input, and n means the number of neurons, w_{ij}, and b_i are the weight coefficients and bias, respectively.

The modeling process is divided into three stages: training, which takes in 70% of the experimental data, testing, which takes in 15% of the experimental data, and

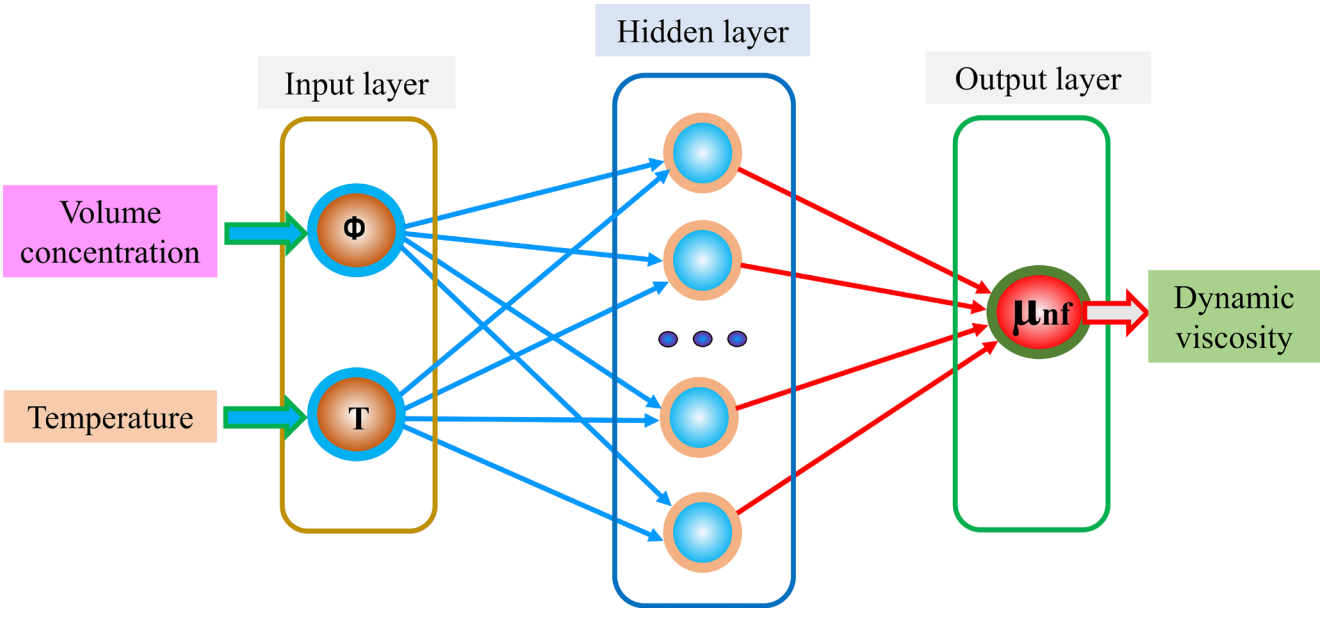

Fig. 2 ANN architecture for predicting μ_{nf} of nanofluid

validation, which takes in another 15% [34]. The ANN model performance is evaluated based on metrics such as the MSE and *R*. For the model to be accurate, the *R* value should be closer to 1, and the MSE should be minimized as much as possible. The dataset utilized for training, testing, and validation comprises 35 data points from experimental datasets. Fig. 3, illustrates the flowchart of the ANN modeling process.

The outputs are generated using input data and weights, followed by a check for accuracy. The modeling process is complete if the outputs meet the required accuracy criteria. However, if the modeling accuracy is deemed insufficient, adjustments are made to the neurons in the hidden layer, and a similar iterative process is undertaken. The optimal network size is determined by heuristics involving the number of neurons.

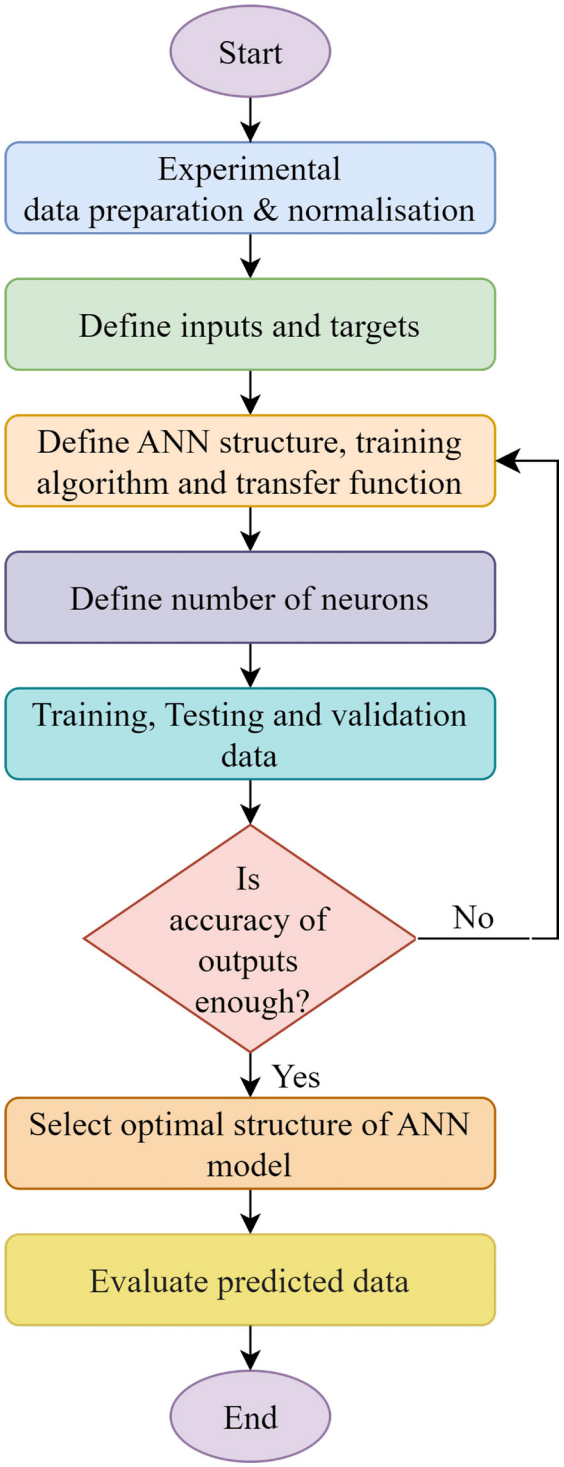

Fig. 3 ANN modeling flowchart

3 Result and discussion

The performance of the ANN improves when the number of neurons in the hidden layer is varied, as shown in Table 3. The number of neurons has an impact on the performance of the ANN structure. The optimal ANN is chosen by evaluating the performance of various network structures to improve the network's precision in data estimation. As previously stated, the ANN architecture for modeling μ_{nf} data was chosen by analyzing MSE and *R* values. The ANN were trained using a hidden layer that contained up to 15 neurons. The optimal architecture chosen a network with hidden layer of 10 neurons. The fluctuation of MSE values across training, validation, and test data iterations is depicted in Fig. 4. The *X*-axis represents that the MSE values and *Y*-axis denotes number of epochs. In this training process, an epoch represents one complete iteration of the entire training dataset. It includes updating the model's weights, processing the data in batches, and carrying out both forward and backward propagation. The number of epochs required for training depends on the complexity of the model and the size of the dataset. It is important to monitor metrics such as loss and accuracy to determine when to stop training. At the start, MSE has a high value, but it gradually diminishes with the increase in epochs. The validation process is ended when the MSE value goes up after a certain number of iterations, indicating that the results were unsuccessful. After determining the best outcome, it is presented as an output. In Fig. 4, training stops at 87 epochs when the MSE value reaches approximately 0.0052691. In Fig. 5, the experimental results of μ_{nf} for nanofluid are depicted across various φ and *T*. This is compared with the predicted data from the ANN training, validation, and testing phases. Also, illustrates a strong agreement between experimental data and the predictions made by the ANN. The results indicate precise training of the ANN, affirming its capability for

Table 3 The ANN performance results with different neuron numbers for predicting μ_{nf}

Neuron number	MSE			*R*			
	Train	Validation	Test	Train	Validation	Test	Overall
5	0.0446	0.0234	0.0667	0.99991	0.99993	0.99982	0.99989
6	0.00325	0.0616	0.016	0.99999	0.99999	0.99994	0.99997
7	0.00727	0.0212	0.0214	0.99998	0.99997	0.99998	0.99998
8	0.000162	0.0204	0.0706	1	0.99988	0.99987	0.99997
9	0.000519	0.0364	0.0257	0.99998	0.99997	0.99998	0.99998
10	**0.0000454**	**0.00527**	**0.0486**	**1**	**1**	**0.99988**	**0.99998**
11	0.000857	0.0938	0.103	0.99985	0.99982	0.99981	0.99982
12	0.00609	0.0916	0.205	0.99999	0.99988	0.99924	0.9999
13	0.00103	0.455	0.389	1	0.99963	0.9996	0.99974
14	0.000919	0.0445	0.0925	1	0.99995	0.99997	0.99996
15	0.00416	0.99	0.269	0.99999	0.99703	0.99919	0.99958

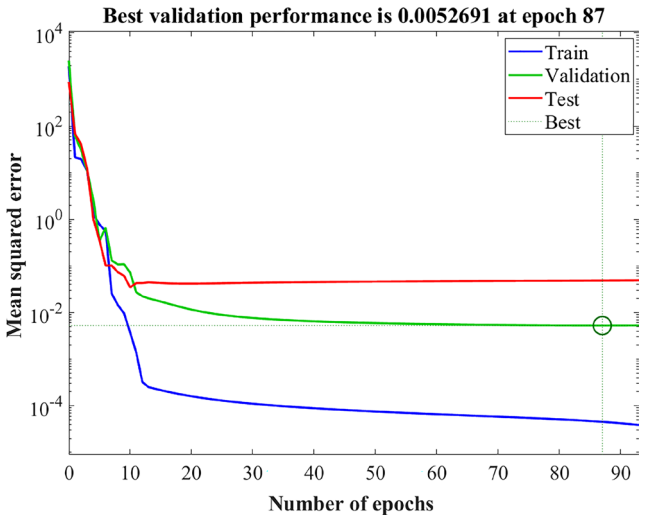

Fig. 4 μ_{nf} prediction using ANN model - MSE plot

accurately predicting the μ_{nf} of nanofluid. The *R*, representing the correlation between the network ANN prediction data and experimental data, is crucial. An ideal value for high quality must be greater than 0.9 [35]. According to the results presented, the *R* for all components of the ANN is approximately 1.

The error histogram in Fig. 6 illustrates the disparity between predicted and experimental data after training with 20 bins on the *X*-axis. Training, validation, and testing data are represented by blue, green, and red bars, respectively. It is 0.00156 at a zero-line error, encompassing a range of errors from −0.3966 to 0.1808. The *Y*-axis (vertical bars) indicates the number of samples, and a zero-error line indicates the precision. Notably, many datasets are close to the zero line, suggesting that the trained model can effectively predict output.

The relationship between input variables (φ and *T*) and response variables (μ_{nf}) is illustrated in Fig. 7, through a three-dimensional surface fit. The surface response can fit all experimental data points. Furthermore, there are noticeable variations in μnf as a result of changes in both φ and *T*.

A mathematical correlation has been developed to determine the μ_{nf} of GnPs-SAE10W oil nanofluids, and Eq. (2) has been formulated in terms of nanoparticle φ and *T*.

$$\mu_{nf} = a - b\cdot\varphi - c\cdot T - d\cdot\varphi^2 + e\cdot\varphi\cdot T - f\cdot T^2 + g\cdot\varphi^2\cdot T - h\cdot\varphi\cdot T^2 + i\cdot T^3 \quad (2)$$

This correlation is obtained through curve fitting method (surface fit) and demonstrates satisfactory accuracy. The correlation coefficients for Eq. (2) are presented in Table 4. The goodness of fit for this correlation is shown in Table 5.

The deviation between experimental and predicted values is evaluated using a percentage error concept based on the results of ANN and correlations. This percentage of error is calculated using the following Eq. (3) [18].

$$\text{Error}(\%) = \left[\frac{\left(\text{Experimental}\left(\mu_{nf}\right) - \text{Predicted}\left(\mu_{nf}\right)\right)}{\text{Experimental}\left(\mu_{nf}\right)}\right]\cdot 100 \quad (3)$$

The error percentages for both ANN and correlation predicted data are shown in Fig. 8. An ANN model have an error percentage that is between −0.89 and 0.66, while correlation error percentages are between −6.74 and 5.27.

The error percentage for ANN shows that they are more accurate in predicting the μ_{nf} of nanofluids than correlation.

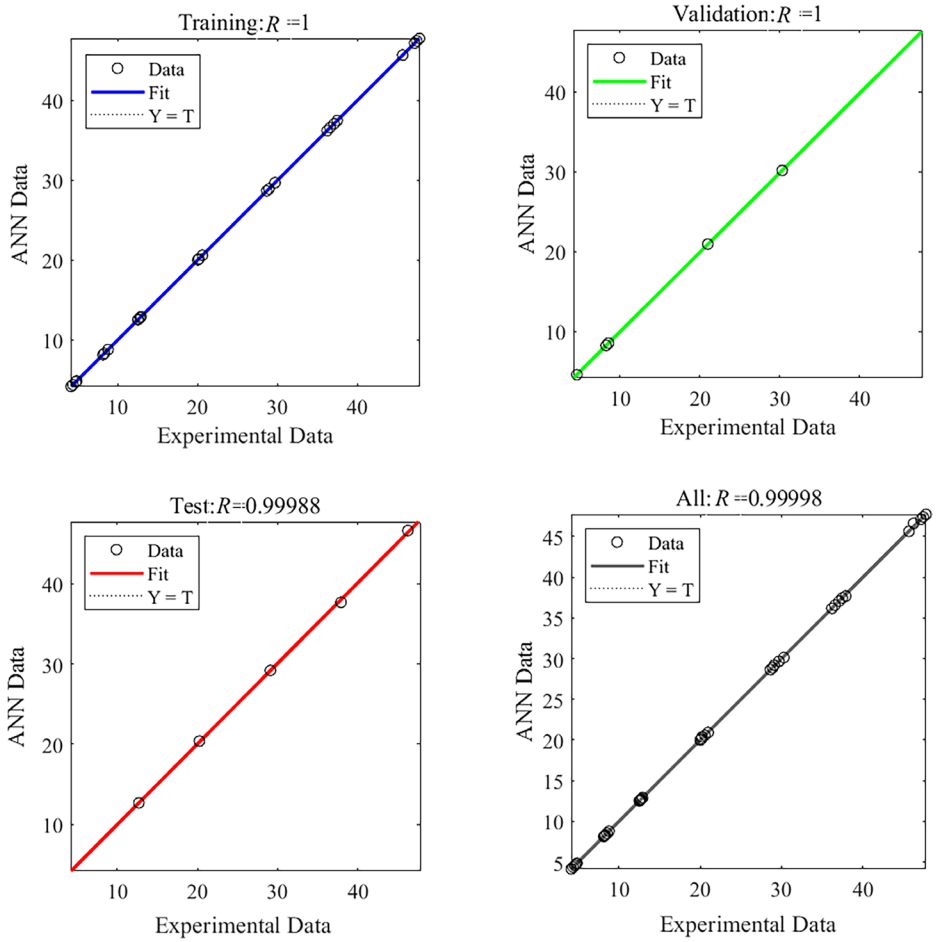

Fig. 5 The correlation coefficient and regression diagram for μ_{nf} prediction in GnPs-SAE10W oil nanofluids

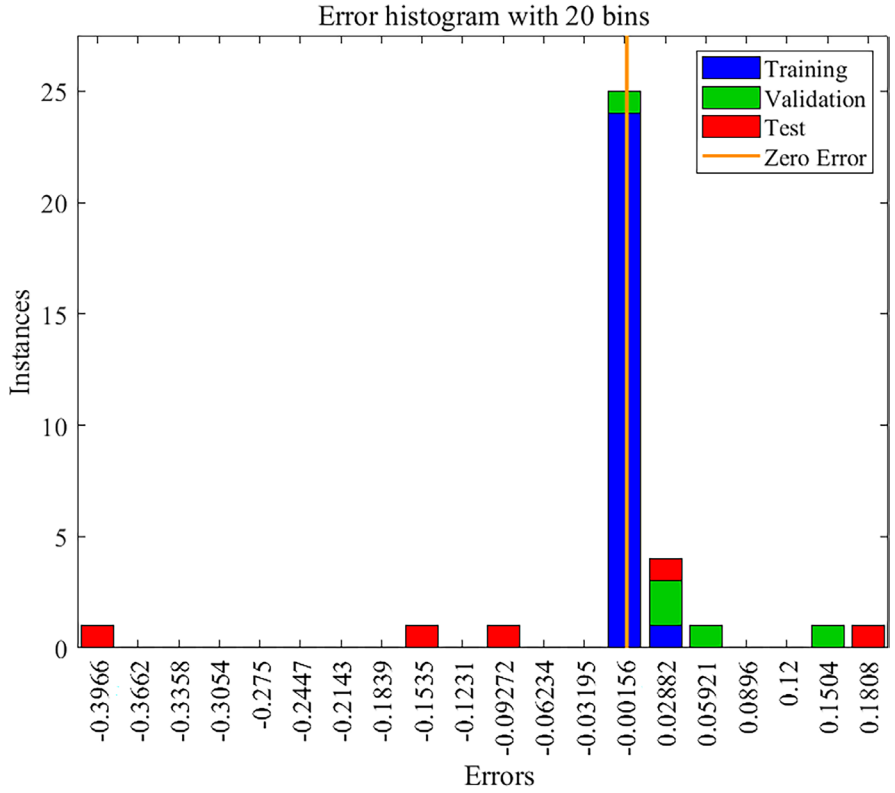

Fig. 6 The ANN error histograms for predicting μ_{nf}

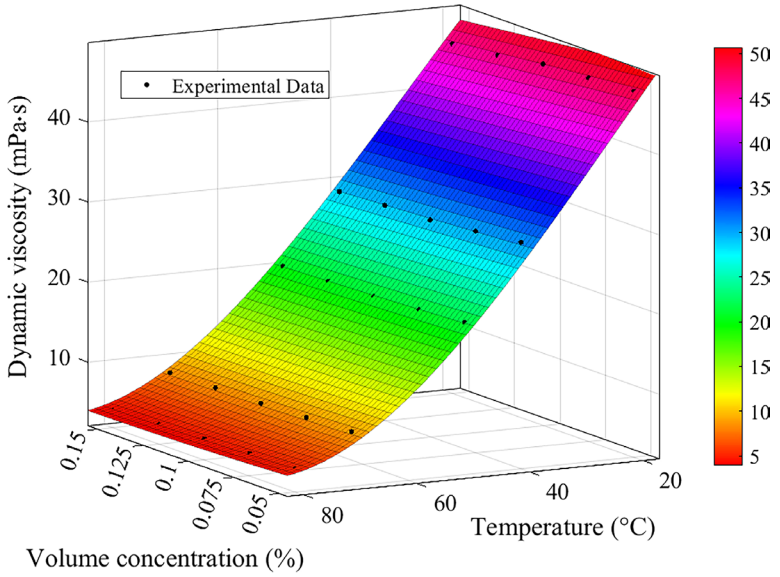

Fig. 7 The 3D surface fitted graph for experimental μ_{nf} of the GnPs/SAE10W oil nanofluids

Table 4 Coefficients of correlation

Coefficients	Value
a	66.8761
b	29.8290
c	0.8154
d	32.9258
e	0.5921
f	0.0059
g	1.0158
h	0.0052
i	0.0001

Table 5 The goodness of fit for correlation

Sum of squared errors (SSE)	R^2	Adjusted R^2	Root mean squared error (RMSE)
7.5855	0.9990	0.9987	0.5401

In Fig. 9, it is shown that the predicted and experimental μ_{nf} of the GnPs-SAE10W oil nanofluid are compared. The plots demonstrate a clear compatibility between the μ_{nf} predicted by ANN and the experimentally determined values. This agreement is significantly more prominent than the μ_{nf} predicted by correlation methods.

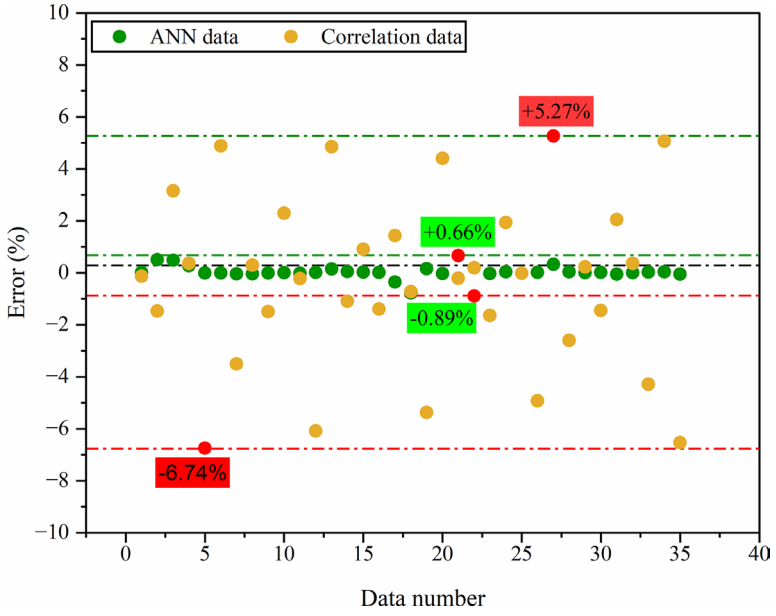

Fig. 8 Error percentages for ANN and correlation data

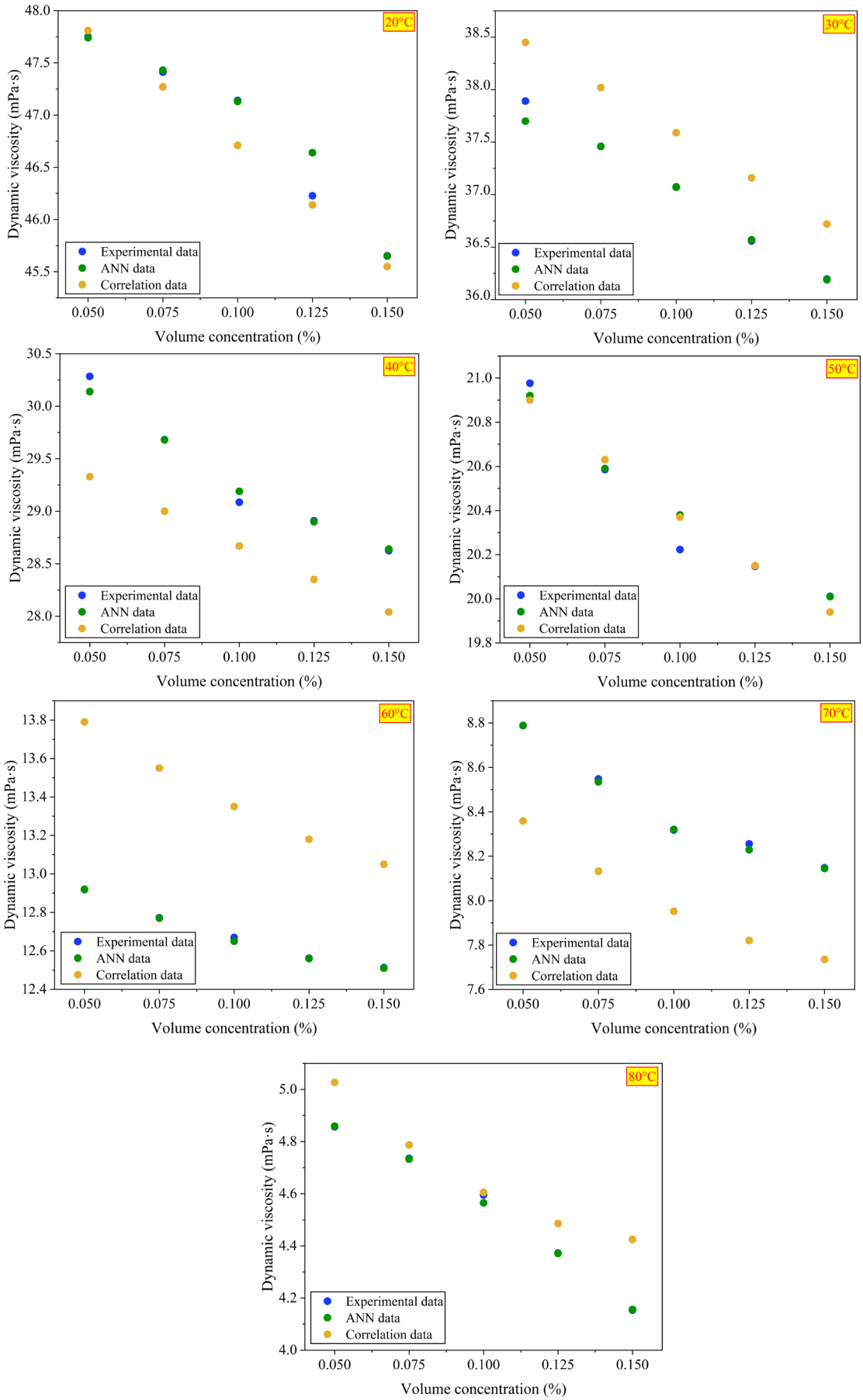

Fig. 9 Comparison between experimental data, ANN, and correlation data

4 Conclusion

This study presents ANN model and a mathematical correlation to predict the dynamic viscosity of GnPs-SAE10W oil nanofluids at different volume concentrations and temperatures. ANN are constructed using neurons determined by a trainlm algorithm in the hidden layer. The best performance was achieved by a hidden layer of 10 neurons. The experimental data was then fitted with curves, and the results were compared with their MSE, RMSE, R, R^2, and maximum error percentages. A neural network achieved R = 0.9998 and MSE = 0.0052691 with a maximum error of 0.66%, outperforming curve fitting methods with R^2 = 0.9990 and RMSE = 0.5401. The error percentages for the ANN model range between −0.89% and 0.66%, while for the mathematical model, they range between −6.74% and 5.27%. With such minimal error rates, the ANN model accurately predicts the dynamic viscosity of graphene/SAE10W oil nanofluids at specified volumes concentrations, and temperatures. It also emphasizes the potential for cost and time savings when compared to experimental approaches.

References

[1] Mousa, M. H., Miljkovic, N., Nawaz, K. "Review of heat transfer enhancement techniques for single phase flows", Renewable and Sustainable Energy Reviews, 137, 110566, 2021. https://doi.org/10.1016/j.rser.2020.110566

[2] Natesan, K., Karinka, S. "A comprehensive review of heat transfer enhancement of heat exchanger, heat pipe and electronic components using graphene", Case Studies in Thermal Engineering, 45, 102874, 2023. https://doi.org/10.1016/j.csite.2023.102874

[3] Ho, M. L. G., Oon, C. S., Tan, L.-L., Wang, Y., Hung, Y. M. "A review on nanofluids coupled with extended surfaces for heat transfer enhancement", Results in Engineering, 17, 100957, 2023. https://doi.org/10.1016/j.rineng.2023.100957

[4] Okonkwo, E. C.,Wole-Osho, I., Almanassra, I. W., Abdullatif, Y. M., Al-Ansari, T. "An updated review of nanofluids in various heat transfer devices", Journal of Thermal Analysis and Calorimetry, 145(6), pp. 2817–2872, 2021. https://doi.org/10.1007/s10973-020-09760-2

[5] Azmi, W. H., Sharma, K. V., Mamat, R., Najafi, G., Mohamad, M. S. "The enhancement of effective thermal conductivity and effective dynamic viscosity of nanofluids – A review", Renewable and Sustainable Energy Reviews, 53, pp. 1046–1058, 2016. https://doi.org/10.1016/j.rser.2015.09.081

[6] Sahoo, R. R., Kumar, V. "Development of a new correlation to determine the viscosity of ternary hybrid nanofluid", International Communications in Heat and Mass Transfer, 111, 104451, 2020. https://doi.org/10.1016/j.icheatmasstransfer.2019.104451

[7] Karami, H., Papari-Zare, S., Shanbedi, M., Eshghi, H., Dashtbozorg, A., Akbari, A., Mohammadian, E., Heidari, M., Sahin, A. Z., Teng, C. B. "The thermophysical properties and the stability of nanofluids containing carboxyl-functionalized graphene nano-platelets and multi-walled carbon nanotubes", International Communications in Heat and Mass Transfer, 108, 104302, 2019. https://doi.org/10.1016/j.icheatmasstransfer.2019.104302

[8] Choi, S. U. S., Eastman, J. A. "Enhancing thermal conductivity of fluids with nanoparticles", In: Siginer, D. A., Wang, H.-P. (eds.) Developments and Applications of Non-Newtonian Flows, 1995: Presented at the ASME International Mechanical Engineering Congress and Exposition, November 12-17, 1995, San Francisco, California", American Society of Mechanical Engineers, 1995, pp. 99–105. ISBN 9780791817421

[9] Ilyas, S. U., Ridha, S., Sardar, S., Estellé, P., Kumar, A., Pendyala, R. "Rheological behavior of stabilized diamond-graphene nanoplatelets hybrid nanosuspensions in mineral oil", Journal of Molecular Liquids, 328, 115509, 2021. https://doi.org/10.1016/j.molliq.2021.115509

[10] Klazly, M., Bognár, G. "A novel empirical equation for the effective viscosity of nanofluids based on theoretical and empirical results", International Communications in Heat and Mass Transfer, 135, 106054, 2022. https://doi.org/10.1016/j.icheatmasstransfer.2022.106054

[11] Dehghani, Y., Abdollahi, A., Karimipour, A. "Experimental investigation toward obtaining a new correlation for viscosity of WO_3 and Al_2O_3 nanoparticles-loaded nanofluid within aqueous and non-aqueous basefluids", Journal of Thermal Analysis and Calorimetry, 135(1), pp. 713–728, 2019. https://doi.org/10.1007/s10973-018-7394-5

[12] Hemmat Esfe, M. "The Investigation of Effects of Temperature and Nanoparticles Volume Fraction on the Viscosity of Copper Oxide-ethylene Glycol Nanofluids", Periodica Polytechnica Chemical Engineering, 62(1), pp. 43–50, 2018. https://doi.org/10.3311/PPch.9741

[13] Esfe, M. H., Esmaily, R., Khabaz, M. K., Alizadeh, A., Pirmoradian, M., Rahmanian, A., Toghraie, D. "A novel integrated model to improve the dynamic viscosity of MWCNT-Al_2O_3 (40:60)/Oil 5W50 hybrid nano-lubricant using artificial neural networks (ANNs)", Tribology International, 178, 108086, 2023. https://doi.org/10.1016/j.triboint.2022.108086

[14] Nguyen, C. T., Desgranges, F., Roy, G., Galanis, N., Maré, T., Boucher, S., Angue Mintsa, H. "Temperature and particle-size dependent viscosity data for water-based nanofluids - Hysteresis phenomenon", International Journal of Heat and Fluid Flow, 28(6), pp. 1492–1506, 2007. https://doi.org/10.1016/j.ijheatfluidflow.2007.02.004

[15] Aberoumand, S., Jafarimoghaddam, A., Moravej, M., Aberoumand, H., Javaherdeh, K. "Experimental study on the rheological behavior of silver-heat transfer oil nanofluid and suggesting two empirical based correlations for thermal conductivity and viscosity of oil based nanofluids", Applied Thermal Engineering, 101, pp. 362–372, 2016. https://doi.org/10.1016/j.applthermaleng.2016.01.148

[16] Wang, Y., Al-Saaidi, H. A. I., Kong, M., Alvarado, J. L. "Thermophysical performance of graphene based aqueous nanofluids", International Journal of Heat and Mass Transfer, 119, pp. 408–417, 2018. https://doi.org/10.1016/j.ijheatmasstransfer.2017.11.019

[17] Soltani, O., Akbari, M. "Effects of temperature and particles concentration on the dynamic viscosity of MgO-MWCNT/ethylene glycol hybrid nanofluid: Experimental study", Physica E: Low-dimensional Systems and Nanostructures, 84, pp. 564–570, 2016. https://doi.org/10.1016/j.physe.2016.06.015

[18] Manikandan, S., Nanthakumar, A. J. D. "Experimental Study of Cu Nanoparticles Loading and Temperature Effects on the Thermophysical Properties of SAE10W oil: Developing a New Mathematical Correlation", Periodica Polytechnica Chemical Engineering, 68(2), pp. 216–229, 2024. https://doi.org/10.3311/PPch.23140

[19] Sahin, F., Genc, O., Gökcek, M., Çolak, A. B. "From experimental data to predictions: Artificial intelligence supported new mathematical approaches for estimating thermal conductivity, viscosity and zeta potential in Fe_3O_4-water magnetic nanofluids", Powder Technology, 430, 118974, 2023. https://doi.org/10.1016/j.powtec.2023.118974

[20] Alfaleh, A., Khedher, N. B., Eldin, S. M., Alturki, M., Elbadawi, I., Kumar, R. "Predicting thermal conductivity and dynamic viscosity of nanofluid by employment of Support Vector Machines: A review", Energy Reports, 10, pp. 1259–1267, 2023. https://doi.org/10.1016/j.egyr.2023.08.001

[21] Shi, L., Zhang, S., Arshad, A., Hu, Y., He, Y., Yan, Y. "Thermophysical properties prediction of carbon-based magnetic nanofluids based on an artificial neural network", Renewable and Sustainable Energy Reviews, 149, 111341, 2021. https://doi.org/10.1016/j.rser.2021.111341

[22] Hua, S., Jasim, D. J., Alizadeh, A., Eftekhari, S. A., Nasajpour-Esfahani, N., Shamsborhan, M., Toghraie, D. "Dynamic viscosity prediction using artificial intelligence for an antifreeze containing MWCNT–alumina hybrid nanopowders", Engineering Applications of Artificial Intelligence, 126, 107046, 2023. https://doi.org/10.1016/j.engappai.2023.107046

[23] Hemmat Esfe, M., Esfandeh, S., Amoozadkhalili, F., Toghraie, D. "Increasing the accuracy of estimating the dynamic viscosity of hybrid nano-lubricants containing MWCNT-MgO by optimizing using an artificial neural network", Arabian Journal of Chemistry, 16(2), 104405, 2023. https://doi.org/10.1016/j.arabjc.2022.104405

[24] Hemmat Esfe, M., Toghraie, D., Amoozadkhalili, F., Alidoust, S. "Optimization of accuracy in estimating the dynamic viscosity of MWCNT-CuO/oil 10W40 nano-lubricants", Egyptian Informatics Journal, 24(1), pp. 117–128, 2023. https://doi.org/10.1016/j.eij.2022.12.006

[25] Chu, Y.-M., Ibrahim, M., Saeed, T., Berrouk, A. S., Algehyne, E. A., Kalbasi, R. "Examining rheological behavior of MWCNT-TiO_2/5W40 hybrid nanofluid based on experiments and RSM/ANN modeling", Journal of Molecular Liquids, 333, 115969, 2021. https://doi.org/10.1016/j.molliq.2021.115969

[26] Bhat, A. Y., Qayoum, A. "Viscosity of CuO nanofluids: Experimental investigation and modelling with FFBP-ANN", Thermochimica Acta, 714, 179267, 2022. https://doi.org/10.1016/j.tca.2022.179267

[27] Fan, G., El-Shafay, A. S., Eftekhari, S. A., Hekmatifar, M., Toghraie, D., Mohammed, A. S., Khan, A. "A well-trained artificial neural network (ANN) using the trainlm algorithm for predicting the rheological behavior of water – Ethylene glycol/WO_3 – MWCNTs nanofluid", International Communications in Heat and Mass Transfer, 131, 105857, 2022. https://doi.org/10.1016/j.icheatmasstransfer.2021.105857

[28] Ebrahim, S. A., Pradeep, E., Mukherjee, S., Ali, N. "Rheological behavior of dilute graphene-water nanofluids using various surfactants: An experimental evaluation", Journal of Molecular Liquids, 370, 120987, 2023. https://doi.org/10.1016/j.molliq.2022.120987

[29] ASTM "ASTM D445-24 Standard Test Method for Kinematic Viscosity of Transparent and Opaque Liquids (and Calculation of Dynamic Viscosity)", ASTM International, West Conshohocken, PA, USA, 2024. https://doi.org/10.1520/D0445-24

[30] Esfe, M. H., Khaje khabaz, M., Esmaily, R., Mahabadi, S. T., Toghraie, D., Rahmanian, A., Fazilati, M. A. "Application of artificial intelligence and using optimal ANN to predict the dynamic viscosity of Hybrid nano-lubricant containing Zinc Oxide in Commercial oil", Colloids and Surfaces A: Physicochemical and Engineering Aspects, 647, 129115, 2022. https://doi.org/10.1016/j.colsurfa.2022.129115

[31] Sharma, P., Said, Z., Kumar, A., Nižetić, S., Pandey, A., Hoang, A. T., Huang, Z., Afzal, A., Li, C., Le, A. T., Nguyen, X. P., Tran, V. D. "Recent Advances in Machine Learning Research for Nanofluid-Based Heat Transfer in Renewable Energy System", Energy & Fuels, 36(13), pp. 6626–6658, 2022. https://doi.org/10.1021/acs.energyfuels.2c01006

[32] Maaoui, W., Mehrez, Z., Najjari, M. "A web-based intelligent calculator for predicting viscosity of ethylene–glycol–based nanofluids using an artificial neural network model", Rheologica Acta, 63(1), pp. 60–63, 2024. https://doi.org/10.1007/s00397-023-01425-9

[33] Pare, A., Ghosh, S. K. "A unique thermal conductivity model (ANN) for nanofluid based on experimental study", Powder Technology, 377, pp. 429–438, 2021. https://doi.org/10.1016/j.powtec.2020.09.011

[34] Cui, W., Cao, Z., Li, X., Lu, L. Ma, T., Wang, Q. "Experimental investigation and artificial intelligent estimation of thermal conductivity of nanofluids with different nanoparticles shapes", Powder Technology, 398, 117078, 2022. https://doi.org/10.1016/j.powtec.2021.117078

[35] Sahebi, S. A. R., Ganji, D. D., Alinezhad, J. "On the thermal performance of nanofluid over a cylinder within a confined channel: The splitter effect", Case Studies in Thermal Engineering, 49, 103275, 2023. https://doi.org/10.1016/j.csite.2023.103275