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Lotfi Snoussi, Olfa Fakhfakh, Mohamed Ibn Khedher. Precise Deep Learning Model for Predicting the Transport Properties of Nanofluids Applied to Enhancing Performance of Thermal Energy Systems. 2023 IEEE International Conference on Artificial Intelligence & Green Energy (ICAIGE), Oct 2023, Sousse, Tunisia. <10.1109/icaige58321.2023.10346403>. <hal-04349927>

**HAL Id: hal-04349927**

**<https://hal.science/hal-04349927v1>**

Submitted on 11 Jan 2024

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# Precise Deep Learning model for predicting dynamic viscosity of Al<sub>2</sub>O<sub>3</sub> nanofluid in Ethylene Glycol/water mixture

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**Abstract**— Compared to other traditional working fluids, nanofluids have better thermal characteristics. The potential use of nanofluids in a variety of engineering domains has been raised by numerous researchers. Accurately determining the dynamic viscosity of nanofluids in a real-time setting is very important for industries that heavily rely on heat transfer and is difficult because of their numerous interdependencies.

In this paper, the Random Forest (RF), a robust machine learning method, and a Deep Neural Network (DNN) model are employed to accurately predict the dynamic viscosity of an Al<sub>2</sub>O<sub>3</sub>/(EG:Water) nanofluids. Our two artificial intelligent models used temperature, volume fraction, nanoparticle size, base fluid, and nanoparticle density as inputs and viscosity as an output. A total of 1220 experimental datasets from the literature were collected and divided into the testing and training groups. The DNN model's predictive performance was assessed against the RF model and various theoretical and empirical correlations. The models' performance was analyzed using various graphical plots and statistical performance metrics. The results obtained confirm that the proposed DNN approach has excellent prediction abilities for nanofluids ( $R^2= 0.9892$ ,  $RMSE = 0.0086$ ,  $AARD\%=12.25$ ).

**Keywords**— Deep Learning, Viscosity prediction, Machine learning, Heat transfer enhancement, Renewable energy

## I. INTRODUCTION

Rapid progress in nanotechnology led to the discovery of nanofluids in 1995 by Choi [1]. These are fluids containing nanosize particles suspended in a base fluid such as ethylene glycol, water, propylene glycol, or oil. Nanofluids have the potential to enhance the performance of various energy-related mediums and technologies, including renewable energy systems [2], air conditioners, and heat pipes. Numerous studies have explored the impact of nanoparticles on the thermal and energy efficiency of renewable energy systems, particularly solar systems [3], as well as their potential for reducing emissions [4].

Dynamic viscosity of nanofluids, as one of the thermophysical properties, describes the resistance of the fluid to flow. For industrial applications, dynamic viscosity has a direct impact on the required pumping power, the convective heat transfer coefficient, and the associated pressure drop in any energy system. Accurately predicting the dynamic viscosity of nanofluids is of paramount importance

for industries that heavily rely on heat transfer, such as microelectronics and cooling applications [5].

Various approaches have been employed for modeling the properties of nanofluids, including regression-based correlations like empirical and theoretical models [6-12], as well as artificial intelligence models like Artificial Neural Networks and Machine Learning. According to the literature review, most empirical correlations were developed to evaluate the thermophysical properties of specific nanofluids within particular temperature and volume fraction ranges, and thus, they are not generalizable to other types of nanofluids [13,14]. Additionally, the empirical and theoretical correlations derived from conventional classical regression techniques often lack sufficient accuracy in estimating the thermal characteristics of nanofluids due to limitations in laboratory investigations and instrumentation errors [15].

Several studies have demonstrated that employing artificial intelligence for modeling yields higher accuracy compared to using empirical correlations. Machine Learning (ML) is one of the AI techniques extensively employed in the literature to model and predict thermophysical properties such as viscosity [16]. ML techniques encompass Deep Learning (DL) [17], Artificial Neural Networks (ANN) [18,19], Group Method of Data Handling (GMDH) [20], Adaptive Neuro-Fuzzy Inference System (ANFIS) [21], metaheuristic optimization algorithms like genetic algorithm (GA) [22] and particle swarm optimization (PSO), CAtegory And Regression Tree (CART) [23], Random Forest (RF) [24], Decision Tree (DT), and Support Vector Machine (SVM) [25], among others.

To the best of the authors' knowledge, there are few publications that have studied the modeling and viscosity prediction of different mixture ratios of ethylene glycol and water-based nanofluids using Deep Learning. Given the advantages of Deep Neural Networks (DNN) – which possess a strong nonlinear mapping ability to establish relationships between input and output variables without explicitly considering the specific physical processes, along with higher training accuracy and faster training speed [26] – this work selects a DNN as a reliable method for predicting the dynamic viscosity of Al<sub>2</sub>O<sub>3</sub> in various mixture ratios of ethylene glycol and water-based fluids.

Firstly, this study compiles and presents the available measurements from various published studies of Al<sub>2</sub>O<sub>3</sub>-EG/water nanofluids with different shapes and sizes. Next, the fundamental theory and modeling process of both the Random Forest and Deep Neural Network are briefly introduced. Lastly, the predicted results of our DNN model are compared with experimental data, existing empirical and theoretical models, and one Machine Learning model.

## II. PROBLEM STATEMENT AND DATASET DISCRPTION

Previous research has revealed that many factors can influence the dynamic viscosity of nanofluids, including nanoparticle volume fraction, nanoparticle size, temperature, nanoparticle type, density of nanoparticles, morphology and base fluid. In this study, experimental data were collected from various references in order to ensure the accuracy of the proposed model. A total of 1178 data sets were used in which the base fluid (BFs), nanoparticles volume fraction ( $\varphi$ ), temperature ( $T$ ), size ( $d_p$ ), density ( $\rho_p$ ) of each nanoparticles as input parameter and dynamic viscosity of nanofluids ( $\mu_{nf}$ ) as output were considered. Table I shows the number of data obtained for Al<sub>2</sub>O<sub>3</sub> and different mixture ratio of ethylene glycol and water (H<sub>2</sub>O:EG) from each reference. The dataset is unbalanced.

TABLE I. DETAILS OF THE USED EXPERIMENTAL DATA FOR PREDICTING THE DYNAMIC VISCOSITY OF NANOFLUIDS.

BFs	T(°K)	Size (nm) & Shape	$\varphi$	$\rho_p$ (Kg/m <sup>3</sup> )	data point
EG [27]	283,15 - 333,15	43; 20 Sphere	0,00124382 - 0,0290033	4000	127
H <sub>2</sub> O/EG (80:20)[28]	273,13 - 333,22	30 Sphere	0,003 - 0,015		75
H <sub>2</sub> O/EG (50:50) [29]	303,05 - 343,25	13 Sphere	0,005-0,02		20
H <sub>2</sub> O/EG (60:40) [28];[29]	303,3 - 343,36 273,09 - 333,09	13 Sphere 30 Sphere	0,005 - 0,02 0,003 - 0,015	3950 ; 3970	95
H <sub>2</sub> O/EG (40:60) [28];[29]	303,3 - 343,36 273,09 - 333,09	13 Sphere 30 Sphere	0,005 - 0,02 0,003 - 0,015	3950 ; 3970	95
H <sub>2</sub> O [30-33];[17]	278,15 - 345,03 288,12 - 323,24 294,15 - 348,15 293,15 - 353,15 283,15 - 345,15	13; 33;65 Sphere 30 Sphere 40;50 Sphere 13 Sphere; 50 Cylinder; 13; 100 Sphere	0,001-0,04 0,0005-0,006 0,001-0,04 0,002 - 0,015 0,0003 - 0,13	3088 ; 3416 3600 ; 3700 3890 ; 3890	783

Table II summarizes the detailed statistics for the input and target variables. The kurtosis and skewness values are in the

considerable range, indicating the ability of the data to provide predictive models.

TABLE II. DESCRIPTIVE STATISTICS OF REFERENCE PARAMETERS FOR PREDICTING THE DYNAMIC VISCOSITY.

Parameters	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis
$\varphi$	0.01697	0.0216	0	0.13061	2.3366	5.5707
T (K)	308.687	17.5339	273.09	353.15	0.2813	0.4522
$d_p$ (nm)	35.3551	15.6154	10	150	1.7674	7.2164
$\mu_{nf}$ (mPa.s)	3.2091	4.75602	0.3995	35.2884	3.1197	11.1728

Fig. I shows the correlation coefficient, also known as the Pearson correlation coefficient, between the dynamic viscosity and the other input variables. This coefficient reflects the dynamic viscosity of the nanofluids, which has the most robust linear relationship with the volume fraction (Pcc = -0.072). The dynamic viscosity of the nanofluid has a strong linear association with the size (Pcc = -0.17) of the nanoparticles when compared to the volume fraction (Pcc = -0.22) of the nanoparticles.

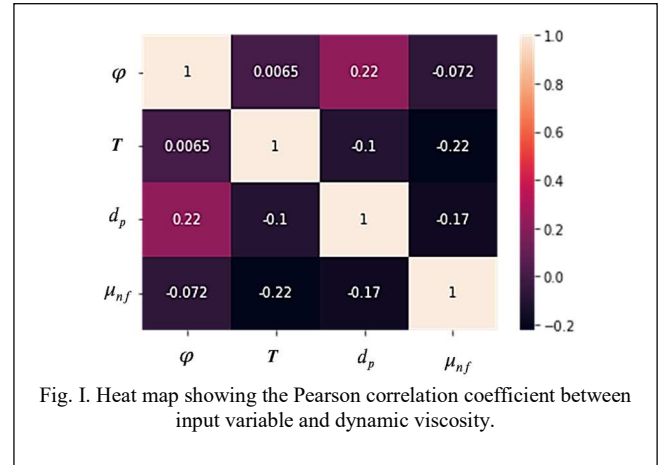


Fig. I. Heat map showing the Pearson correlation coefficient between input variable and dynamic viscosity.

The flowchart of soft computing techniques to predict the dynamic viscosity of nanofluids is illustrated in Fig. II.

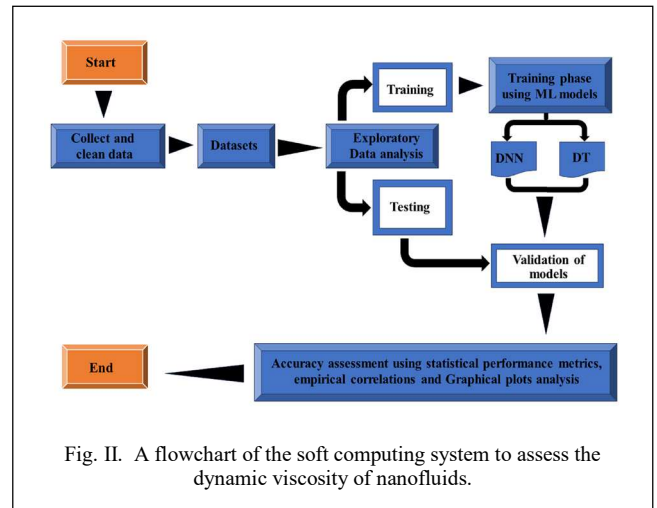


Fig. II. A flowchart of the soft computing system to assess the dynamic viscosity of nanofluids.

### III. AI MODEL DEVELOPMENT METHODOLOGY

#### A. Random forests model

RF model is an effective learning algorithm employing an ensemble of decision trees introduced by Breiman (2001) [34]. RF is commonly employed in two classes, namely regression and classification. Random forests are built on an ensemble of decision trees that split data hierarchically using simple conditional statements; these decisions are interpretable and fast to analyze at scale. The decision tree has a significant shortcoming which is the overfitting. Overfitting can be avoided by replacing the decision tree with RFs. Furthermore, when compared to other regression models, the RF technique is high-speed and reliable [35].

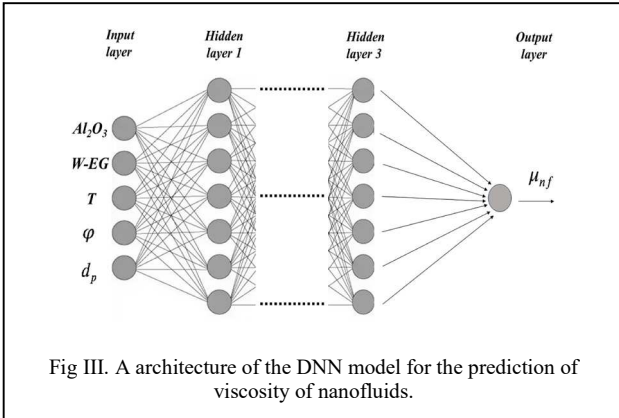
#### B. Deep Neural Network model

Deep Neural Network (DNN) is a class of machine learning algorithms similar to the artificial neural network with several hidden layers located between the input and output layers. Each layer has a set number of units (neurons) that perform a specific functional transformation on the input. These models can approximate the behavior of any function. Through a set of weights ( $w_{i,k}$ ), a bias ( $b$ ), and a non-linear activation function ( $f$ ), the output ( $y$ ) of a unit ( $i$ ) in layer ( $l$ ) is connected to the output ( $x$ ) of the earlier layer ( $k$ ) with  $J$  outputs.

$$y_i^l = f \sum_{j=1}^J w_{i,k} x_k + b_i$$

DNNs have substantial advantages over classic machine learning techniques such as support vector machines, decision trees, RF, and k-nearest neighbors in extracting features at different levels of abstraction and thereby learning more complex patterns. To efficiently extract input data features, DNNs compute their internal parameters in the forward pass and then iteratively refine them during backpropagation.

A DNN-based prediction model is developed in this work to predict the dynamic viscosity of  $Al_2O_3$  in several base-fluids. For DNN model, the system takes as input a vector of fore parameters (Temperature, Diameter of the Nanoparticle, Nanoparticle Volume Fraction and Base Fluid). The model then predicts the viscosity as the output. Figure III illustrates the architecture of our deep learning approach consisting of an input layer, a output layer, and three hidden layers with respective sizes of 500, 100, and 50 neurons.



#### C. Model assessment Criteria

In order to evaluate the performance and accuracy of the RF and Deep learning models, several statistical metrics are employed which include the coefficient of determination ( $R^2$ ), Root Mean Squared Error (RMSE) and Average Absolute Relative Deviation (AARD %).

$$R^2 = 1 - \frac{\sum_{k=1}^N (\mu_{pre,k} - \mu_{exp,k})^2}{\sum_{k=1}^N (\mu_{pre,k} - (\bar{\mu}_{exp,k}))^2}$$

$$RMSE = \sqrt{\frac{\sum_{i=0}^{N-1} (\mu_{pre,i} - \mu_{exp,i})^2}{N}}$$

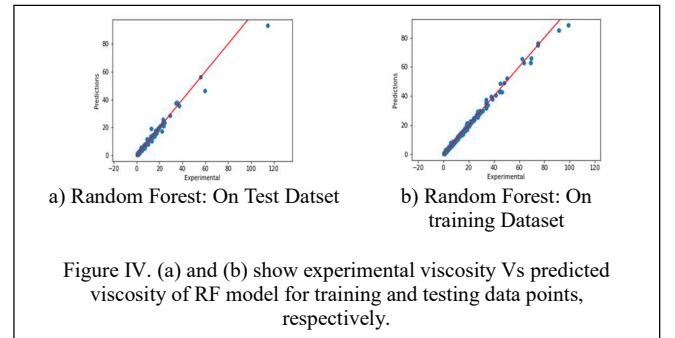
$$AARD(\%) = \frac{100}{N} \sum_{k=1}^N \frac{|\mu_{pre,k} - \mu_{exp,k}|}{\mu_{exp,k}}$$

### IV. RESULTS AND DISCUSSION

The main goal of this research is to develop accurate and reliable deep learning model's for predicting the dynamic viscosity of nanofluids. As mentioned previously the accuracy of the AI model depends on various inputs parameters. In the two Machine learning models developed in this work , base fluid ( $BFs$ ), nanoparticles volume fraction ( $\varphi$ ), temperature ( $T$ ), size ( $d_p$ ), density ( $\rho_p$ ) of each nanoparticles are considered as input parameter and dynamic viscosity of nanofluids ( $\mu_{nf}$ ) as output variable.

#### A. Analysis of Model Accuracy

In order to assess and compare the performance of the developed AI models, various graphical analyses and statistical score metrics were thoroughly implemented. As graphical analysis, Figure IV and V illustrate the accuracy of viscosity predictions by RF and DNN models,



respectively.

The values of dynamic viscosity are displayed in a scatter diagram where the experimental viscosity is taken along the horizontal axis and the predicted viscosity by our Deep Neural Network or Random Forest model's is taken along the vertical axes.

The plots reflect the models' precision in relation to the training (right) and testing (left) datasets. A comparison of the scatter plots shows that our DNN model has the best fit between predicted nanofluids viscosity and experimental data.

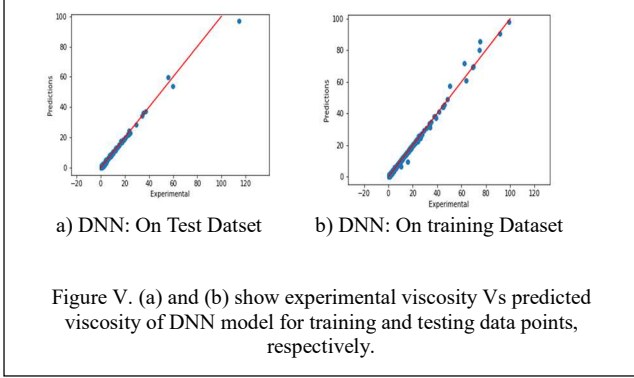


Figure VI.a depicts the loss history of the training and testing stages. In numerous epochs, the loss for testing or validation data performed quite similarly to the loss for training data.

The root mean square error (RMSE) is also determined and shown in Figure VI.b at each stage of the training and testing procedure. As a result, it is apparent that the issue of overfitting does not exist in this suggested DNN model. So, this DNN model can accurately predict the viscosity of nanofluids and may be used without completing any actual experiments.

The statistical criteria RMSE,  $R^2$  and AARD are given in

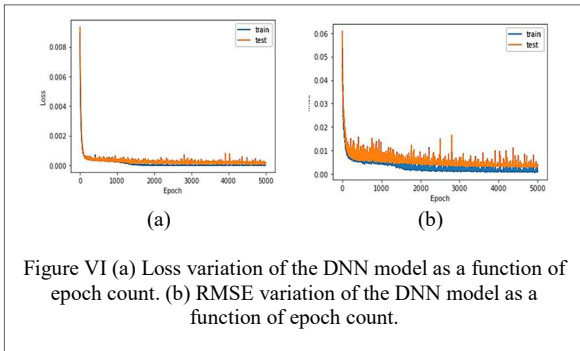


Table III confirm the efficiency and robustness of the DNN model in comparison with RF model. The results demonstrate that our DNN approach outperforms one standard machine learning model, RF, as indicated by the RMSE metrics, for example. In fact, our DNN achieves an RMSE of 0.0086, which is 35% lower than RF approach, with an RMSE of 0.0135.

TABLE III. PERFORMANCE OF DNN MODEL IN COMPARISON WITH RF.

Classifier	RMSE	$R^2$	AARD%
RF	0.0135	0.9718	12.83
DNN	0.0086	0.9892	12.25

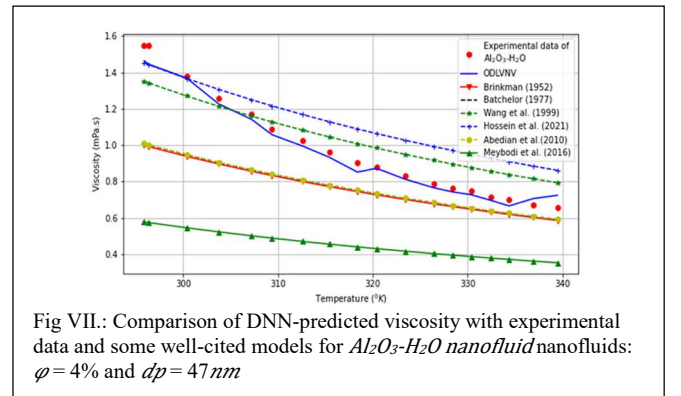
### B. DNN model compared with regressive correlation models

With the intention of evaluating the prediction performance of the proposed soft computing model, a comparison with some empirical and theoretical models has been carried out. Numerous researchers, cited in table IV have conducted theoretical and experimental analyses of the thermophysical characteristics of nanofluids. A few traditional models for the dynamic viscosity that took temperature, volume fraction, and nanoparticle size into account were put forth.

TABLE IV. THE LITERATURE PUBLISHED MODELS EMPLOYED FOR COMPARISON IN THE CURRENT STUDY.

Model	Correlation
Brinkman [6]	$\mu_{nf} = \frac{\mu_{bf}}{(1-\varphi)^{2.5}}$ For a very low volume fraction ( $\varphi < 0.04$ )
Batchelor [7]	$\mu_{nf} = \mu_{bf}[1 + 2.5\varphi + 6.5\varphi^2]$ Considered isotropic suspension of rigid and spherical nanoparticles
Wang et al [8]	$\mu_{nf} = \mu_{bf}[1 + 2.5\varphi + 6.2\varphi^2]$ For the viscosity of nanofluids for a particle volume fraction $\varphi < 0.03$
Hossein et al [9]	$\frac{\mu_{nf}}{\mu_{bf}} = 1.1015(1 + \varphi)^{9.053} \left(1 + \frac{T_{nf}}{70}\right)^{0.095} \left(1 + \frac{d_p}{0.275}\right)^{-0.027}$ Valid for different amount of water and EG-based nanofluids : $5^\circ\text{C} \leq T_{nf} \leq 70^\circ\text{C}$ ; $(5 \text{ nm} \leq d_p \leq 150 \text{ nm})$ ; $(1\% \leq \varphi \leq 5\%)$
Abedian et al [10]	$\mu_{nf} = \frac{\mu_{bf}}{1 - 2.5\varphi}$ Newtonian fluid with a single rigid spherical particle
Meybodi et al [11]	$\frac{\mu_{nf}}{\mu_{bf}} = \frac{A_1 + A_2 \exp\left(\frac{\varphi}{S}\right) + A_3 \exp\left(\frac{\varphi}{S}\right)^2 + A_4 \exp\left(\frac{\varphi}{S}\right)^3}{A_5 + A_6 \times \frac{\ln(S)}{T} + A_7 \frac{(\ln(S))^2}{T}}$ Viscosity of water-based CuO, TiO <sub>2</sub> , Al <sub>2</sub> O <sub>3</sub> and SiO <sub>2</sub> nanofluids.
Sharma et al [12]	$\frac{\mu_{nf}}{\mu_{bf}} = C_1 \left(1 + \frac{\varphi}{100}\right)^{11.3} \left(1 + \frac{T_{nf}}{70}\right)^{-0.038} \left(1 + \frac{d_p}{170}\right)^{-0.061}$ For a wide range of nanofluids containing Cu, CuO, TiO <sub>2</sub> , SiC, ZrO <sub>2</sub> and Al <sub>2</sub> O <sub>3</sub> nanoparticles of different sizes, concentrations and temperatures dispersed in water:

Fig VII shows how the dynamic viscosity of nanofluids decreases as operating temperature rises. The DNN model also agrees with the outcomes of the experiments. Among the tested models, only the Hossein et al. and Meybodi models [9,10] considered temperature.



For a particle size of 30 nm and a volume concentration of 1% for an Al<sub>2</sub>O<sub>3</sub>/ H<sub>2</sub>O -EG of (60:40) ration nanofluid, Fig .VIII demonstrates that only the proposed Deep Neural

Network (DNN) method could predict the same trend for the experimental data, and the other models are unable to account for the effect of temperature on dynamic viscosity. As a result, this analysis shows that our DNN model is more reliable over a wide temperature range.

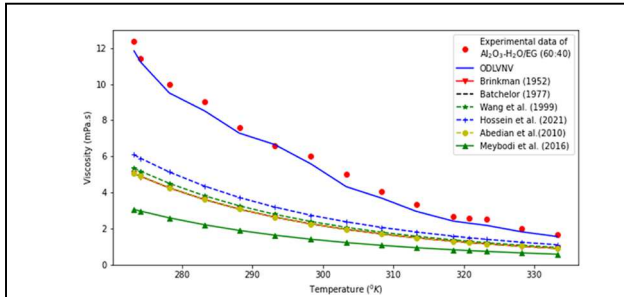


Fig. VIII: Comparison of DNN-predicted viscosity with experimental data and some well-cited models for  $\text{Al}_2\text{O}_3/\text{H}_2\text{O-EG}$  of (60:40) ratio:  $\varphi = 1\%$  and  $dp = 30\text{nm}$ .

The results of Fig IX demonstrate that the dynamic viscosity of the  $\text{Al}_2\text{O}_3\text{-EG}$  nanofluid significantly increases as a function of the nanoparticle volume fraction, increasing the need for pumping energy [36]. In fact, the dynamic viscosity of an  $\text{Al}_2\text{O}_3\text{-EG}$  nanofluid with cylindrical nanoparticles (diameter  $dp = 50\text{nm}$ ) is lower than that of one with spherical particles ( $dp = 13\text{nm}$ ).

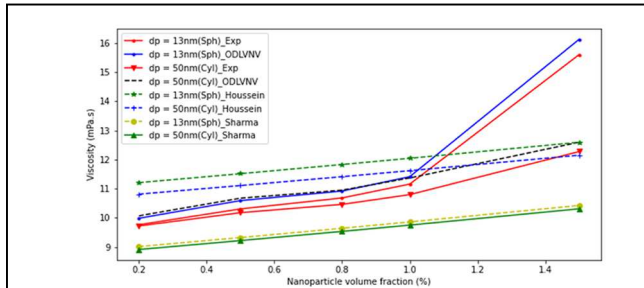


Fig. IX: Comparison of DNN-predicted viscosity with experimental data and some well-cited models for  $\text{Al}_2\text{O}_3/\text{EG}$  nanofluids ( $dp = 13\text{nm}(\text{Sph})$ ;  $dp = 50\text{nm}(\text{Cyl})$ ) and  $T = 313.15\text{-K}$ .

The 3D contour map depiction of dynamic viscosity of the proposed DNN model is shown in Fig. X versus the independent input parameters, namely temperature and

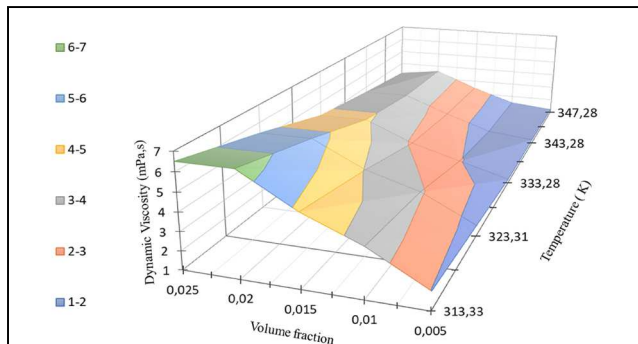


Fig. X : The three-dimensional surf diagram with dynamic viscosity output..  $\text{Al}_2\text{O}_3/\text{H}_2\text{O-EG}$  (60:40);  $dp = 13\text{nm}$

volume fraction. The untrained points are shown by the colored portion of the mesh surface. The diagrams supplied for the trained DNNs lead to the conclusion that the DNN model can be appropriately regarded as an approximation function of the dynamic viscosity for the problem's output. Additionally, it should be noted that the temperature parameter has little impact on dynamic viscosity, especially in the case of small concentrations of nanoparticles. However, when the volume percentage of nanoparticles grows, so does the effect of temperature, which raises dynamic viscosity, reaching a value of approximately  $6.5027\text{mPa.s}$  at a volume fraction of  $0.025\%$  and a temperature of  $313.33\text{°K}$ .

TABLE V. THE AARD% AND RMSE OF DIFFERENT MODELS

	AARD	DNN	[6]	[7]	[8]	[9]	[10]	[11]
<b>RMSE</b>								
<b>Fig. VII</b>		7.13	19.97	19.24	12.61	18.67	19.16	52.59
<b>Fig. VIII</b>		0.07	0.27	0.26	0.12	0.16	0.26	0.57
		7.42	56.21	56.18	53.63	46.82	56.18	72.58
		0.37	3.94	3.94	3.78	3.36	3.94	5.02

TABLE VI. THE AARD% AND RMSE OF DIFFERENT MODELS FOR  $\text{Al}_2\text{O}_3/\text{EG}$  NANOFLUID

Metrics	DNN		[9]		[12]	
	13nm	50nm	13nm	50nm	13nm	50nm
<b>RMSE</b>	0.32	0.45	1.71	0.85	2.49	1.21
<b>AARD%</b>	15.06	4.21	12.90	7.62	14.36	10.46

For the three nanofluids types examined when varying temperature for two nanoparticle size, tables V and VI reveal that the DNN model gives the lowest values of AARD% and RMSE compared to other theoretical and empirical models.

## V. CONCLUSION

This study aimed to develop AI-based models based on Deep Learning to accurately predict the dynamic viscosity of  $\text{Al}_2\text{O}_3$  nanofluids in Ethylene Glycol/water mixtures using an extended database from previous studies. A machine learning method like Random Forest was employed to further validate the model's accuracy.

The model's performance was subsequently evaluated using various statistical criteria and graphical plots. Additionally, several cited classical and empirical correlations were used as comparative models to assess the accuracy of dynamic viscosity prediction.

Based on the study's results, the following conclusions can be drawn:

- The performance evaluation, as indicated by results obtained from statistical analysis and graphical approaches ( $R^2 = 0.9892$ ,  $\text{RMSE} = 0.0086$ ,  $\text{AARD}\% = 12.25$ ), confirms that the proposed DNN approach exhibits remarkable predictive abilities for nanofluids.
- The dynamic viscosity of  $\text{Al}_2\text{O}_3/\text{EG-H}_2\text{O}$  nanofluids, across all data points, shows a strong dependence on nanoparticle volume fraction. However, the intrinsic properties of the nanoparticles, including diameter (size) and temperature, are of crucial importance in predicting dynamic viscosity.

iii) The outcomes demonstrate that the DNN model is consistent with experimental data, and that the viscosity of nanofluids decreases as temperature rises.

These findings constitute a significant step toward understanding how nanofluids function and how they might be enhanced to meet future industrial demands. Such advancements have the potential to enhance energy performance and heat transfer efficiency, as well as system design and optimization.

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