Measurement of the dynamic viscosity of water-based nanofluids containing Al_2O_3, TiO_2, and ZnO using the Artificial Neural Network method

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Abstract

Nanofluids are strong candidates as heat carriers due to their excellent thermophysical properties. Among these thermophysical properties, viscosity is critical in heat transfer and pressure loss calculations. In this study, three different water-based nanofluids, Al_2O_3, TiO_2, and ZnO, were prepared with volumetric concentrations ranging from 0.1% to 1%. The dynamic viscosities of these nanofluids were experimentally measured within a temperature range of 20 °C to 50 °C. Artificial neural networks (ANN) were employed to predict the results based on the experimental data. Two different approaches were applied in the implementation of the ANN method. The first approach involved creating three separate ANN models, each dedicated to predicting the viscosities of the three different nanofluids. The second approach used a single generalized ANN to predict the viscosities of all nanofluids. The results were evaluated using the criteria of R-squared (R^2) and root mean square error (RMSE) values. In all models, R^2 values exceeded 99%, while the RMSE values were calculated for the Al_2O_3, TiO_2, and ZnO nanofluid ANN models and the generalized ANN model to be 0.40%, 0.30%, 0.04%, and 0.28% respectively. These results demonstrate that a nanofluid's viscosity can be effectively predicted individually and multiple nanofluids using an ANN model.

Keywords: Artificial neural network, nanofluid, dynamic viscosity, aluminum oxide, titanium dioxide, zinc oxide.

1. Introduction

Advanced developments in industrial technology and the global commercial race require that the heat exchangers should have ultra-high heat exchange capability. However, conventional fluids such as water, oil, and alcohol being used as the heat carriers in the heat exchangers are

insufficient to ensure the ultra-high heat transfer rate. One of the most innovative ways to deal with this problem is to enhance the thermal conductivity of the fluid. Choi and Eastman [1] claimed in 1995 that metallic nanoparticles suspended in a conventional heat transfer fluid increase the thermal conductivity of the fluid. The same researchers called the resulting suspension to be nanofluid for the first time in the literature. Nanofluid is a suspension obtained by adding nanomaterials such as metal (Al, Cu, Ni, Au, Ag, etc.), metal-oxide (Al_2O_3, TiO_2, CuO, NiO_2, Fe_2O_3), and polymer with diameters ranging from 1 nm to 100 nm to increase the thermal conductivity of different fluids (water, oil, alcohol, etc.) [2].

The addition of nanoparticles to conventional fluids not only changes the thermal conductivity but also affects the other properties of the same fluids, such as specific heat, density, and viscosity, which are vital thermophysical properties in heat transfer calculation. Viscosity is a property that is essential in the determination of the Reynolds number, which is a dimensionless number used to calculate the convection heat transfer coefficient and the pressure drop in the fluid flow. Therefore, the dynamic viscosity of the nanofluids should be known. In addition, metal oxides are the most preferred nanoparticles in nanofluids, also called metal-oxide-based nanofluids, as they are more economical and more stable than metallic nanoparticles [3, 4]. Metal oxide-based nanofluids can also be prepared as nanofluids with single, hybrid, or ternary components [5]. Studies on the determination of the dynamic viscosity of metal oxide-based nanofluids continue intensively. Khodadadi et al. experimentally measured the dynamic viscosity of MgO-water nanofluid for the first time, and med that the base fluid showed Newtonian rheological behavior, and the nanofluid showed non-Newtonian rheological behavior [6]. Moldoveanu et al. [7] experimentally determined the dynamic viscosity of Al_2O_3 (at volume concentrations of 1%, 2,%, and 3%) and SiO_2 (at volume concentrations of 1%, 3,%, and 5%) metal-oxides dispersed water-based nanofluids called mono-component nanofluids, and mixtures of these metal-oxides (at volume concentration 0.5% Al_2O_3 + 0.5%SiO_2 and 0.5%Al_2O_3 + 1.5%SiO_2) dispersed water-based nanofluids called bi-component nanofluids. They emphasized that the viscosity of the SiO_2 nanofluid was less than both the Al_2O_3 and bi-component nanofluids, and the temperature increase decreased the dynamic viscosity. In another study, the dynamic viscosity of the hybrid nanofluid, in which Al_2O_3-ZnO nanoparticles dispersed in different mixing ratios (2:1, 1:1, and 1:2), was measured experimentally with Brookfield DV-I

PRIME digital viscometer at the temperature range of 25 °C and 65 °C and the volumetric concentration of 0.33% and 1.67% [8]. The dynamic viscosity of the hybrid nanofluid increased with the increase in volumetric concentration and decreased with increasing temperature, and the 1:1 mixing ratio had the lowest viscosity. In a recent study, the dynamic viscosity of a hybrid nanofluid consisting of a ternary mixture of Al_2O_3, CuO, and TiO_2 nanoparticles has measured at a volume fraction of 0.01% - 0.1% and a temperature range of 35-50 °C, and compared with the viscosities of nanofluids formed by single and double combinations of these nanoparticles [9]. Increasing on volume fraction increased cluster formation, besides viscosity increased due to intrinsic viscous stresses.

Experimentally determining the viscosity of a nanofluid for different concentration ratios, different temperatures, and different nanoparticle types is both laborious and expensive. Therefore, theoretical models, empirical correlations, or computer-aided models are preferred in determining the viscosity of nanofluids in the literature [10-12]. Although theoretical and empirical correlations are used in predicting the viscosity of the nanofluids, these correlations may always not predict the viscosity of the nanofluids exactly. Therefore, researchers try to predict the thermophysical properties of nanofluids, including viscosity, by developing computer-aided models. One of the most prominent computer-aided models is ANN, based on the heuristic model. The ability of ANNs to determine the underlying complex relationships of the complex structure provides an opportunity to better predict the viscosity of the nanofluid than empirical correlations [13]. Ramezanizadeh et al. [14] reviewed the machine learning approaches used to predict the dynamic viscosity of nanofluids and emphasized that ANN-based models yield more precise results. In the same study, it was claimed that the accuracy of the results obtained with the ANN model depends on the selection of appropriate input variables. Besides, it was claimed that temperature, volume concentration, shear rate, and size of nanoparticles were the most influential factors in ANN models. Also, temperature and volume concentration are generally defined as input variables when developing ANN models to predict the dynamic viscosity of metal oxide-based nanofluids. For instance, the input variables in dynamic viscosity estimation of nanofluids such as ethylene glycol-water mixture Al_2O_3 [14], aqueous nanofluid of TiO_2 [15], and ZnO-ethylene glycol nanofluid [16] in ANN model were temperature and volume concentration. Aminian [17] assigned temperature, concentration, nanoparticle density, and nanoparticle size as input variables in the dynamic viscosity estimation with ANN of eight

different nanofluids collected from various references in the literature. In addition, sufficient data is needed for validation and generalization purposes of making ANN models effective. Esfe et al. highlighted that artificial intelligence algorithms, particularly ANN, which offer advantages such as high accuracy and reliable predictions, can be utilized to more accurately and rapidly determine the thermo-physical properties of nanofluids [18]. Wang and Chen emphasized the extensive research conducted on the thermo-physical properties of nanofluids, particularly viscosity and thermal conductivity, highlighting the frequent use of ANN and genetic algorithm methods for their determination [19]. They also stressed the critical importance of conducting experimental data over a broader range. In another study, a data set was created by measuring the thermal conductivity of nanoparticles with different volumetric ratios at different temperatures. The generated data set was used in ANN training. In addition, an algorithm was proposed to optimize the number of neurons in the hidden layer. As a result, a correlation coefficient of 0.993861 was obtained for all outputs using ANN architecture with 8 neurons in the hidden layer [20]. Ruhani et al. investigated the variation of thermal conductivity of cerium oxide/ethylene glycol nanofluid at different temperatures and concentrations. They compared the predictability of thermal conductivity using ANN and fitting methods. Experiments showed that the thermal conductivity ratio (TCR) of the nanofluid increases with increasing φ and temperature. They emphasized that the ANN model has a higher predictive ability than the fitting method [21]. Tian et al. investigated the predictability of thermal conductivity of graphene oxide-Al_2O_3/water-ethylene glycol hybrid nanofluid using Perceptron feedforward ANN. As a result, they predicted high accuracy with an average correlation coefficient of 1.67e-6 for MSE and 0.999 for thermal conductivity [22].

Following an extensive review of the current state of the literature, it's apparent that while individual ANN-based predictions for the dynamic viscosities of various metal oxides exist in the open literature, there's a notable absence of studies demonstrating the prediction of various metal oxides using a single ANN methodology. Consequently, research aims to provide a scientific foundation for the precise prediction of dynamic viscosities in nanofluids containing different nanoparticles, specifically water-based Al_2O_3, TiO_2, and ZnO nanofluids, using a single high-precision ANN model. The study comprises the preparation of three nanofluids, along with the measurement of their dynamic viscosities across a range of temperatures and concentrations.

The ANN model is constructed to predict these viscosities, incorporating temperature, concentration, and a less common factor, relative density, as input variables. Two prominent aspects set this article apart: the inclusion of relative density in the model, which is not commonly seen in similar studies, and the development of an ANN model that predicts the viscosity of each nanofluid in a single ANN model. The rest of the article proceeds as follows: In Section 2, the process of preparing nanofluids, conducting measurements, and establishing the ANN methodology is comprehensively presented. Section 3 presents the results along with a discussion of their advantages and limitations. Section 4 summarizes the key findings of the study.

2. Material and method

2.1 Nanoparticles

In the study, Al_2O_3, TiO_2, and ZnO nanoparticles with 99.5-99.9% purity and 13-25 nm average particle size were used to prepare water-based nanofluids. The nanoparticles rise to prominence with their high surface area, geometry, and thermal stability [23, 24]. The properties of the nanoparticles are given in Table 1. FElTecnai G2 spirit bio(TWlriJ) transmission electron microscope (TEM, 120kV) and FEI Quanta FEG 450 (30kV) scanning electron microscope (SEM) were used to characterize the morphological properties of Al_2O_3, TiO_2, and ZnO nanoparticles. TEM and SEM images of the nanoparticles are shown in Figure 1, and it is seen that the particles are spherical, white, and smaller than about 50 nm.

Table 1. Properties of the nanoparticles [25].

Figure 1. SEM and TEM images of nanoparticles

2.2 Preparation of the nanofluids

Nanofluids are of great importance in cooling and heating systems. The tendency of nanoparticles to precipitate in the base fluid is called agglomeration because of its activity and Van der Waals bonds between nanoparticles [26, 27]. Due to the agglomeration in the nanofluid, clogging and contamination occur in the pipes. This may result in reduced system performance and increased energy consumption. To avoid all these negative effects, methods such as one-step

and two-step methods were developed for the ideal preparation and stabilization of nanofluids. The two-step method is the most preferred method by researchers in terms of ease of operation and cost advantages. The two-step method is the process of dispersing nanoparticles, previously obtained by mechanical, physical, and chemical methods, into a base fluid and undergoing a series of treatments [28-30]. In this study, Al_2O_3, TiO_2, and ZnO nanoparticles were dispersed in pure water selected as the base fluid, and five different volumetric concentrations of water-based nanofluid as 0.1%, 0.3%, 0.5%, 0.7%, and 1.0% were prepared. The number of nanoparticles for each volumetric concentration was determined by using Equations (1-5) and prepared by weighing on a precision balance.

$$\phi = \frac{\forall_{np}}{\forall_{nf}} = \frac{\rho_{nf} - \rho_{bf}}{\rho_{np} - \rho_{bf}} \tag{1}$$

$$\rho = \frac{m}{\forall}. \tag{2}$$

$$m_{nf} = m_{np} + m_{bf}. \tag{3}$$

$$\phi_w = \frac{m_{np}}{m_{nf}}. \tag{4}$$

$$\phi = \frac{\forall_{np}}{\forall_{nf}} = \frac{m_{np} / \rho_{np}}{m_{nf} / \rho_{nf}} = \frac{\rho_{nf}}{\rho_{np}}.\frac{m_{np}}{m_{nf}} = \frac{\rho_{nf}}{\rho_{np}}.\phi_w. \tag{5}$$

where ϕ is the volumetric concentration (%), $\forall$ the is volume (m^3), ρ is density (kg/m^3), ϕ_w is mass contribution ratio (%), *nf* is nanofluid index, *np is* nanoparticle index, *bf* is base fluid index.

In the preparation of nanofluids, nanoparticles were added to the pure water selected as the base fluid at the rate specified for each concentration and mixed for half an hour in a magnetic stirrer, as seen in Figure 2(a). The magnetic stirrer was insufficient for the ideal dispersion of solid nanoparticles dispersed in the base fluid. In Figure 2(b), homogenization was performed for 30 minutes at ambient temperature (25 ^oC) in a 20 kHz 500 W ultrasonic homogenizer (IVYMEN CY-500W) to completely split the nanoparticle clusters and prevent agglomeration [31]. Sodium dodecyl sulfate (SDS) was used as a surfactant and stabilizer which is the most commonly used

chemical surfactant in the literature. Due to good stability, high thermal conductivity and low viscosity, the surfactants TMAH, SDS, and SLS are recommended for water-based nanofluids [32-34]. In Figure 3, nanofluids prepared at five different volume concentrations are illustrated.

Figure 2. (a) Magnetic Stirrer (b) Ultrasonic stirrer.

Figure 3. Nanofluids are prepared a various volume concentrations

2.3 Validation

Before measuring the dynamic viscosity of water-based nanofluids, a validation experiment was conducted with pure water to validate the measurement results of the AND-SV10 viscometer. In this context, the dynamic viscosity of pure water was measured in the viscometer and compared with the known reference dynamic viscosity of pure water [35]. In Figure 4, the deviation between the experimentally measured dynamic viscosity of pure water and the reference values is less than 3%, indicating the reliability of the measurements obtained.

Figure 4. Comparison of experimental viscosity values of pure water with reference values.

2.4 Measurement of viscosity

The AND-SV10 (1–1000 mPa.s) viscometer given in Figure 5(a) was used for dynamic viscosity measurements. Three repetitive measurements were conducted for each sample, and the results monitored on the viscometer screen were ensured to remain within 3% accuracy. As seen in Figure 5(b), the viscometer probe and the nanofluid were immersed in a hot water bath (JSRC-22C) to measure the viscosity of the nanofluids at different temperatures and bring them to the desired temperature.

Figure 5 a) Viscometer b) Placement of the viscometer in the heat bath.

The following steps were followed in measuring the viscosity of each nanofluid. First, 100 mL of distilled water was poured into a 250 mL glass beaker and placed in a heat bath for the desired temperature. After the temperature stabilized, calibration was performed at the relevant

temperature using the calibration feature of the viscometer with pure water. This process was repeated at least three times to ensure that the results monitored from the screen remained within 3% accuracy [36]. After the instrument calibration, five different volumetric concentrations of nanofluids were prepared for one type of nanoparticle. The water-based nanofluid was prepared for each concentration ratio and was expected to reach the desired temperature by adjusting the heat bath temperature. After the temperature was stabilized again, the viscosity of the nanofluid was measured at least three times, and the average of the measurements was taken.

2.5 ANN-based predictive methodology

ANN can be defined as an information processing system that works similarly to the biological nervous system. ANN is a system consisting of interconnected artificial nerve cells. Although ANN networks are an algorithm based on training and learning, it is a popular method used in many fields such as computer science, medicine, and control systems [37-39]. Thanks to the ANN's training mechanism, learning and finding solutions according to the learned information, output values can be produced by calculating the information given to the system. Artificial nerve cells, developed to model the functioning of the biological nerve cell mathematically, consist of simple elements whose information processing process is called neurons. Connections between neurons transmit signals. Each connection between neurons has a weight value. It is based on the assumption that the net output of each neuron is obtained by passing its net input through an activation function [40, 41].

In ANN models, inputs are given externally to the network. These inputs are multiplied by weights, and they are all added together. Then, after they are processed in a transfer function appropriate for the problem, they are again spread as output to the external environment (Figure 6) [42, 43].

Figure 6. ANN basic elements and the input/output layer of the model.

In ANN, neurons consist of five main parts: input values (X_n), weights (W_n), bias (b), summation function (Σ), activation function ($f(\Sigma)$) and output (y). All neural networks are derived from this basic structure. Differences in this structure allow ANNs to be classified. The learning ability of

an artificial neural depends on the appropriate adjustment of weights within its chosen algorithm. The neuron output is calculated using Equation (6):

$$y_j = f(\sum_{i=1}^{n} W_{j,i} + b_j). \quad (6)$$

The essential features of ANN are its ability to model nonlinear structures, its parallel distributed structure, its ability to learn and generalize, its adaptability to different problems, and its fault tolerance. One of the practical features of the ANN is that it enables linear or nonlinear modeling of the ANN, thanks to the preferred activation function for the artificial nerve cells that consist of the ANN. Another feature of ANN is that it reveals the hidden relationships in the data structure by using the data related to the problem [44, 45].

Multi-layer perceptron model is a widely preferred model in the ANN model due to its satisfying results in the modeling of nonlinear systems [46, 47]. This architecture consists of three layers: an input layer, a hidden layer, and an output layer [48]. The number of neurons in the input and output layers is based on the nature of the problem. In this study, the input layer has three neurons to be the relative density, temperature, and volume concentration of nanofluids, and the output layer has one neuron to be the dynamic viscosity of nanofluids (Figure 6). The number of hidden layers and neurons directly affects the prediction ability of the ANN. However, there is no general rule for the number of hidden layers and the number of neurons in the hidden layer, and they are determined by trial and error [49, 50]. The network characteristics of the ANN model are summarized in Table 2.

Table 2. Network characteristics of the ANN model.

In this study, the required data for modeling the ANN model were obtained by experimentally measuring the dynamic viscosity of nanofluids. The relative density, temperature, and volume concentration of nanofluids were used in the input layer, which was developed using 105 experimental data, each nanofluid consisting of 35 experimental data, and the dynamic viscosity nanofluid was used in the output layer. At first, the ANN model was designed for each nanofluid containing 35 data sets. The parameters (hidden layer/neurons at hidden layer) in this ANN

model were determined using related literature [51-58]. Secondly, a new ANN model was built with 105 data sets for three different nanofluids. For the evaluation of the statistical performance of the ANN, R-squared (R^2) and the root mean square error (RMSE) values were calculated as to be given in Equations (7) and (8) [59].

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (k_{\exp(i)} - k_{ANN(i)})^2}{\sum_{i=1}^{N} (k_{\exp(i)} -)^2} \quad (7)$$

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{\left| k_{\exp(i)} - k_{ANN(i)} \right|^2}{N}} \quad (8)$$

3. Results and discussion

The dynamic viscosity of water-based Al_2O_3, TiO_2, and ZnO nanofluids was measured experimentally at 0.1%, 0.3%, 0.5%, 0.7% and 1.0% volumetric concentrations and different temperatures ranging from 20 to 50 ℃. The data set prepared with the experimental data was used

of the nanofluids in the input layer and the dynamic viscosity in the output layer. In addition, the model was optimized by using different training functions, single/double hidden layers, and different neuron numbers in hidden layers.

3.1 Experimental results of dynamic viscosity

The variation of experimentally measured dynamic viscosity of water-based Al_2O_3, TiO_2, and ZnO nanofluids are given in Figure 7 (a), (b) and (c) at volumetric concentrations of 0.1%, 0.3%, 0.5%, 0.7% and 1.0% and temperature range of 20 to 50 ^oC. It is obvious that the dynamic viscosity of the nanofluids changes between 0.53 mPa.s and 1.11 mPa.s. As the temperature increases, the dynamic viscosity decrease; on the contrary, the dynamic viscosity increases as the volumetric concentration increases. The decrease in molecular adhesion forces due to temperature increase causes to decrease in the dynamic viscosity of nanofluids. Besides, as the temperature increases, both the specific volume of water increases, and therefore the distance between nanoparticles also increases, and the movement of the base fluid molecules and

nanoparticles increases. These reasons reduce the shear stress resulting from the interaction of nanoparticles and liquid molecules; therefore, the dynamic viscosity of nanofluids decreases. The increase in volumetric concentration, on the other hand, causes an increase in the number of nanoparticles per unit volume, which in turn causes an increase in shear stress. In addition to this, the level of agglomeration is the function of the shear stress. The reasons mentioned can also be explained as the increase in dynamic viscosity with the increase in volumetric concentration. The increase in viscosity causes a pressure drop in the flow, which causes an increase in the pumping power consumed. Finally, as can be seen from the figures, the dynamic viscosity of nanofluids was measured to be Al_2O_3, TiO_2 and, ZnO respectively, from largest to smallest.

Figure 7. The variation of dynamic viscosity of Al_2O_3 (a), TiO_2 (b), and ZnO (c) nanofluids as a function of temperature and volume concentration.

3.2 Optimization of ANN Model

The characteristics of the developed ANN model, which was developed for each nanofluid, were determined separately by examining the literature [51-58]. The ANN model consists of one hidden layer and 17 neurons in the hidden layer (Table 3). No changes were made to the input and output layers. In order to evaluate the performance of the ANN Model, R^2 and RMSE values were calculated and compared with the literature. As a result, high performance was observed, and the usability of the ANN model was proven.

Table 3 . Characteristics of the ANN model for each nanofluids.

The optimum ANN model for all nanofluids was found through the trial and error method. In the study, 36 models were established by changing trainlm (Levenberg-Marquardt), trainbr (Bayesian regularization backpropagation), and trainbfg (BFGS Quasi-Newton) training algorithms and the number of hidden layers/neurons in the hidden layer. The characteristic of the ANN model is listed in Table 4.

Table 4. Characteristics of the ANN model.

Figure 8(a) shows the variation of RMSE, and Figure 8(b) shows the variation of R^2 statistical performance criteria with training algorithms and the number of hidden layers/neurons in the

hidden layer for test data. Low RMSE (close to 0) and high R^2 values (close to 1 but < 1) should be preferred in determining the best ANN model [60]. Trainbr algorithm model inferred poor performance on the test data. Among the training algorithms, the best performance was obtained in tarainlm algorithm. Evaluation from the hidden layer and the number of neurons in the hidden layer perspective, poor performance was determined in low neuron numbers both in one hidden layer and two hidden layer models. Accordingly, it can be said that as the number of neurons increases, more effective learning occurs between the input and output values of the algorithm [54]. However, although the number of neurons continues to increase, performance improvement cannot be achieved. ANN model indicated the best performance when using trainlm algorithm with [12 8] number of neurons in two of the hidden layers. Optimum values of the ANN model characteristics affecting the performance of the model considerably are listed in Table 5.

Figure 8. Variation of RMSE (a) and R^2 (b) at ANN Models for training data.

Table 5. The characteristics of the best ANN model.

Figure 9 illustrates ANN predicted values and experimental values for training data of Al_2O_3, TiO_2, ZnO and Al_2O_3 + TiO_2 + ZnO nanofluids, respectively. The closer data to the fit curve means that the data was predicted more accurately. The viscosity training correlations of Al_2O_3, TiO_2 and ZnO nanoparticle added nanofluids were obtained with 99.998%, 99.994 and 99.995% accuracy. The determination of the dynamic viscosity of three different nanofluids in a single model was calculated with an accuracy of 99.094%. When the results were compared with the literature, it was reported that the correlation coefficient for the prediction of thermal conductivity using ANN according to the cerium oxide/ethylene glycol nanofluid concentration ratio and temperature was very close to 1 (high accuracy) and was in agreement with the experimental results [21]. In the study using Graphene oxide-Al_2O_3/ Water-Ethylene glycol hybrid nanofluid, the average for MSE is 1.67e-6 and the correlation coefficient for a thermal conductivity is 0.999 with the trainbr training algorithm [22]. In the study with SiO2 /water-ethylene glycol (50:50) nanofluid, with 8 neurons in the hidden layer, the correlation coefficient for all outputs is 0.993861 [20]. As a result, it can be said that the results of the study are in line with the literature. It is a fact that the problem becomes more complex with the inclusion of

various nanoparticles. Although the accuracy of the single model is poor, an ANN model in which as many nanofluids as possible may be more practical. It may increase the generalization ability of the ANN model.

In addition, it is expected that a faster and more accurate prediction of the dynamic viscosity of different nanofluids can be achieved by expanding the database.

Figure 9. Experimental values vs ANN predicted values for train data.

3.3 Optimization of ANN Epoch Number and Test Results

Another parameter in ANN models is the epoch number at the training process. Increasing the number of epochs increases the ANN performance to a certain point while increasing the solution time. Figure 10 illustrates the performance of the epoch number for Al_2O_3, TiO_2, and ZnO nanoparticle reinforced aqueous nanofluids. In Figure 10, the statistical performance parameters of R^2 and RMSE are graphed as a function of epoch number. The least and the furthest epoch numbers were set at 1000 and 15000, respectively. A sharp improvement in model performance was obtained between 1000 and 2500 epoch numbers, while it declined slightly between 2500 and 5000. There was no performance improvement afterward. Accordingly, the optimum epoch number was determined to be 5000.

Figure 10. Effect of epoch's number on ANN model performance.

3.4 ANN model performance

Table 6 lists the values of RMSE and the R^2 for test results of selected ANN models. Considering the test results in Table 6, it is seen that the established ANN model has high success performance.

Table 6. Performance of test results.

Figure 11(a), (b), (c) present the dynamic viscosity predicted by the ANN model and the experimentally measured dynamic viscosity on the same graph for Al_2O_3, TiO_2, and ZnO nanofluids, respectively. The matching ability of the curves in the figures means that the ANN model predicts the experimentally measured viscosity in high success. The most important

conclusion drawn from the graphs is that the ANN model can achieve the best prediction for the ZnO nanofluid. Figure 11(d) illustrates the dynamic viscosity values estimated by the ANN model, including all nanofluids and the experimentally measured dynamic viscosity values of all nanofluids in the same graph. Although there are minor deviations, most of the results predicted by the ANN model seem to agree with the experimental results.

Figure 11. Comparison of experimental and predicted ANN dynamic viscosity of a) Al_2O_3, b) TiO_2, c) ZnO, d) all nanofluids.

4. Conclusion

Three different water-based nanofluids, Al_2O_3, TiO_2, and ZnO, with varying concentrations, were experimentally tested for dynamic viscosity across a temperature range. ANN were harnessed for predictive modeling, with two approaches: individual ANN models for each nanofluid and a generalized model for all. The study encompassed a large dataset of 105 experiments and utilized relative density, temperature, and nanoparticle concentration as input parameters. Various ANN configurations were explored to optimize the prediction accuracy, highlighting the robustness and effectiveness of this approach in nanofluid viscosity prediction. The key findings of the study can be summarized as follows:

- The dynamic viscosity of the nanofluids was measured between 0.53 mPa.s and 1.11 mPa.s. The dynamic viscosity of the nanofluid increased with increasing volumetric concentration and decreased with increasing temperature. The dynamic viscosity of each nanofluid increased compared to pure water.
- When the temperature increased from 20 °C to 50 °C, the decrease in dynamic viscosity of pure water was 45.0%, while the decrease in dynamic viscosity for water-based Al_2O_3, TiO_2, and ZnO nanofluids at 1% volume concentration was 40.0%, 29.7%, and 42.4%, respectively.
- R^2 and RMSE values were calculated in the ANN model established for each nanofluid separately as 0.99999990 and 0.0000796 for Al_2O_3, 0.9774794 and 0.0122366 for TiO_2, and 0.9645589 and 0.0149701 for ZnO, respectively.
- According to the optimization made on the ANN model that includes all nanofluids, the best ANN model was the one with two hidden layers, the neurons in the hidden layer [12 8], and the training function 'trainlm'. In dynamic viscosity prediction, the R^2 and RMSE

values in the training data were calculated to be 0.99933 and 0.0021353, while 0.99700 and 0.00280667 in the test data, respectively.

In addition to the effect of nanofluids on improving heat transfer, the high dynamic viscosity increases the pumping power. Therefore, accurate estimation of the dynamic viscosity of nanofluids is vital. The high agreement between the ANN model established and the experimental data in the study will assist the optimum nanofluid selection in reducing the energy consumption in nanofluid applications preferred by academic and industrial environments.

Future work could focus on the development of more accurate soft computational models for water-based nanofluid and also include more varieties of nanoparticles. The same approach can be used to determine the thermophysical properties of hybrid and more nanoparticle-doped nanofluids. Moreover, a larger number of input parameters affecting the thermophysical properties of nanofluids can be considered for model development.

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Biographies

Beytullah Erdoğan was born in 1983 in Karaman in Turkey. He graduated with a bachelor's degree from Firat University in 2006. He got his master's degree at University of New Hampshire in 2010, and also he got his Ph.D. in 2016 from Zonguldak Bülent Ecevit University. His field of interest is heat transfer in mini microchannels and vehicle cooling systems. In addition, he has studied homogenous preparation and thermophysical properties of nanofluids for use in cooling systems. He has been working as an assistant professor at Zonguldak Bülent Ecevit University since 2017.

Oğuz Koçar was born in 1982 in İstanbul. He is a lecturer in Mechanical Engineering at the Engineering Faculty of Zonguldak Bülent Ecevit University, Turkey. Oğuz KOÇAR obtained Ph.D on the optimization of the formability of Al sheet materials using ANN at Sakarya University. He obtained his M.Sc degree from the university of Karaelmas, on formability of Al pipes using shock wave and has a B.Sc degree in Mechanical Engineering from Karabük University. In the projects he took part in, formability, microstructure characterization, material selection, FEM solutions, 3D Printing, CAD and CAM etc. contributed in different fields.

Halil Ibrahim Topal graduated with a bachelor's degree from Nigde University in 2009. In 2013, he completed his master's degree, followed by obtaining his Ph.D. in 2019, all from Zonguldak Bülent Ecevit University. His research interests include district heating, thermodynamic analyses and optimization of multi-generation thermal energy systems, as well as nanofluids.
Commencing his academic career in 2011 at Zonguldak Bülent Ecevit University, Halil Ibrahim Topal is currently pursuing postdoctoral research on advanced district heating systems at the Technical University of Denmark, Thermal Energy Section with a scholarship awarded by the Scientific and Technological Research Council of Turkey (TÜBİTAK) in 2023.

Table List

Table 1. Properties of the nanoparticles [25].

Nano particle	Density (kg/m^3)	Thermal Cond (W/mK)	Purity	Average Size (nm)	Surface Area (m^2/g)	Geometry
Al_2O_3	3890	46	>%99.8	13-20	85-115	Spherical
TiO_2	3900	10	>%99.5	10-25	200-240	Spherical
ZnO	5606	54	>%99.9	18	40-70	Spherical

* Values are obtained from the manufacturer.

Table 2. Network characteristics of the ANN model.

Characteristics	Characteristic for each nanofluid	For three nanofluid
ANN morphology	Multi-layer perceptron	Multi-layer perceptron
Feedforward	Feed-forward	Feed -forward
Training method	Backpropagation	Backpropagation
Error criteria	Mean square error (MSE)	Mean square error (MSE)
Number of Hidden layers/neurons	1 layer / 17 neuron	2 layer / 12 8 neuron
Hidden layer transfer function	Tansig	Tansig/ logsig
Output layer transfer function	Purelin	Purelin
Training method	Trainlm	Trainlm
Number of training/validation data	28	84
Number of test data	7	21

Table 3. Characteristics of the ANN model for each nanofluids.

Nanofluids	Neorun number of HL	Training Function	HL	OL	R^2	RMSE
Al_2O_3	17	Trainlm	Tansig	Purelin	0.9999990	0.0000796
TiO_2	17	Trainlm	Tansig	Purelin	0.9774794	0.0122366
ZnO	17	Trainlm	Tansig	Purelin	0.9645589	0.0149701

HL: Hidden layer, OL: Output Layer

Table 4. Characteristics of the ANN model.

	Hidden Layer		Training Function	Hidden Layer	Output Layer	Performance	
	1st Layer	2st Layer				R^2	RMSE
1	9	x	Trainbr	Tansig	Purelin	0.99878	0.0028814
2	9	x	Trainlm	Tansig	Purelin	0.99928	0.0022193
3	9	x	Trainbfg	Tansig	Purelin	0.99897	0.0026466
4	13	x	Trainbr	Tansig	Purelin	0.99878	0.0028811
5	13	x	Trainlm	Tansig	Purelin	0.99930	0.0021873
6	13	x	Trainbfg	Tansig	Purelin	0.99899	0.0026185
7	17	x	Trainbr	Tansig	Purelin	0.99878	0.0028810
8	17	x	Trainlm	Tansig	Purelin	0.99928	0.0022193
9	17	x	Trainbfg	Tansig	Purelin	0.99901	0.0025983
10	21	x	Trainbr	Tansig	Purelin	0.99898	0.0026287
11	21	x	Trainlm	Tansig	Purelin	0.99932	0.0021538
12	21	x	Trainbfg	Tansig	Purelin	0.99899	0.0026249
13	25	x	Trainbr	Tansig	Purelin	0.99878	0.0028808
14	25	x	Trainlm	Tansig	Purelin	0.99932	0.0021503
15	25	x	Trainbfg	Tansig	Purelin	0.99906	0.0025334
16	29	x	Trainbr	Tansig	Purelin	0.99878	0.0028808
17	29	x	Trainlm	Tansig	Purelin	0.99932	0.0021514
18	29	x	Trainbfg	Tansig	Purelin	0.99907	0.0025154
19	33	x	Trainbr	Tansig	Purelin	0.99878	0.0028807
20	33	x	Trainlm	Tansig	Purelin	0.99933	0.0021408
21	33	x	Trainbfg	Tansig	Purelin	0.99904	0.0025496
22	6	4	Trainbr	Tansig/Logsig	Purelin	0.99883	0.0028225
23	6	4	Trainlm	Tansig/Logsig	Purelin	0.99927	0.0022221
24	6	4	Trainbfg	Tansig/Logsig	Purelin	0.99883	0.0028173
25	8	8	Trainbr	Tansig/Logsig	Purelin	0.99876	0.0029008
26	8	8	Trainlm	Tansig/Logsig	Purelin	0.99923	0.0022880
27	8	8	Trainbfg	Tansig/Logsig	Purelin	0.99892	0.0027045
28	10	6	Trainbr	Tansig/Logsig	Purelin	0.99878	0.0028783
29	10	6	Trainlm	Tansig/Logsig	Purelin	0.99933	0.0021365
30	10	6	Trainbfg	Tansig/Logsig	Purelin	0.99884	0.0028069
31	12	8	Trainbr	Tansig/Logsig	Purelin	0.99878	0.0028796
32	12	8	Trainlm	Tansig/Logsig	Purelin	0.99933	0.0021353
33	12	8	Trainbfg	Tansig/Logsig	Purelin	0.99886	0.0027871
34	14	10	Trainbr	Tansig/Logsig	Purelin	0.99878	0.0028770
35	14	10	Trainlm	Tansig/Logsig	Purelin	0.99933	0.0021374
36	14	10	Trainbfg	Tansig/Logsig	Purelin	0.99902	0.0025858

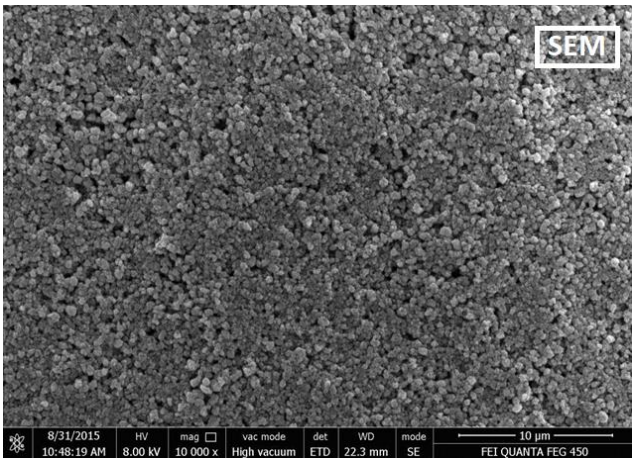
Table 5. The characteristics of the best ANN model.

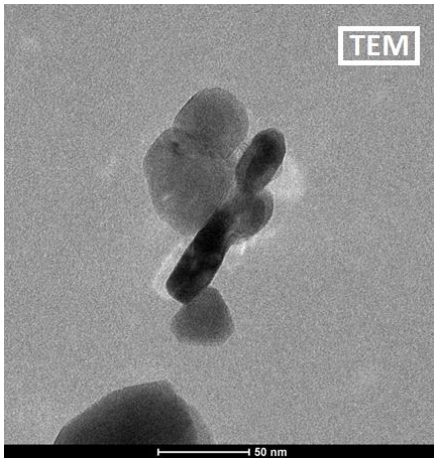
Characteristics	Optimum Level
Number of hidden layer	2
Number of neurons hidden layers	[12 8]
Number of iterations	4559
Max number of iterations	5000
Learning rate	0.001
Train algorithm	Trainlm
RMSE	0.0022
R^2	0.993

Table 6. Performance of test results.

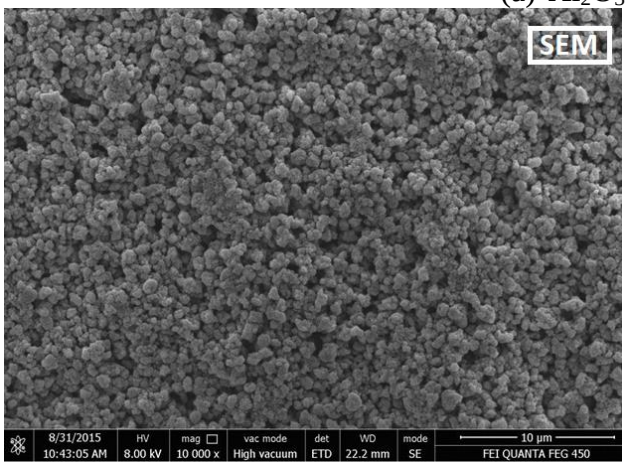
Nanofluids	Number of Epochs	R^2	RMSE
AL_2O_3	5000	0.997340171	0.004070922
TiO_2	5000	0.997910374	0.003070465
ZnO	5000	0.999927106	0.000479723
All nanofluids	5000	0.997003867	0.002806677

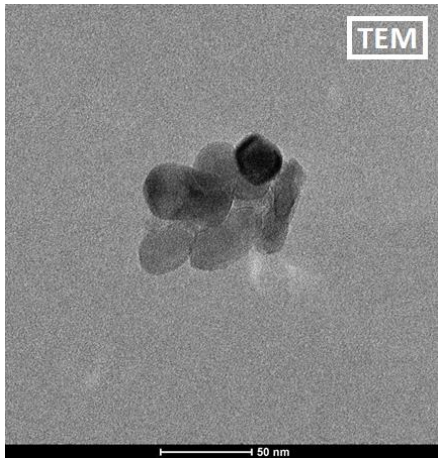
Figure List



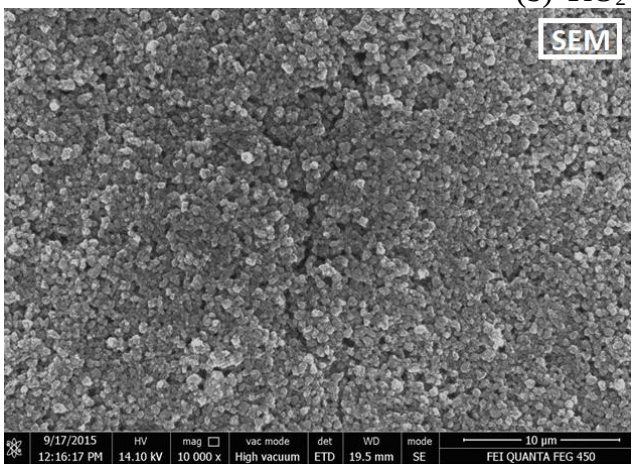


(a) Al_2O_3





(b) TiO_2



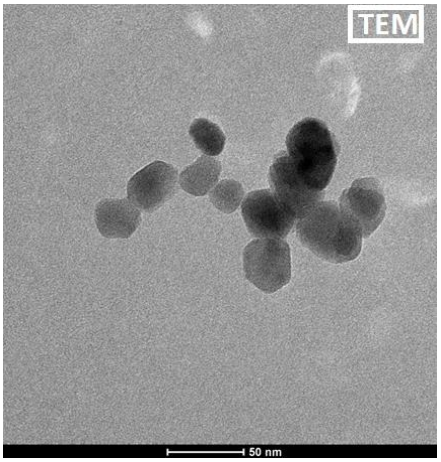


Figure 1. SEM and TEM images of nanofluids and nanoparticles
a) Al_2O_3 b) TiO_2 c) ZnO

(a) (b)

Figure 2. (a) Magnetic Stirrer (b) Ultrasonic stirrer.

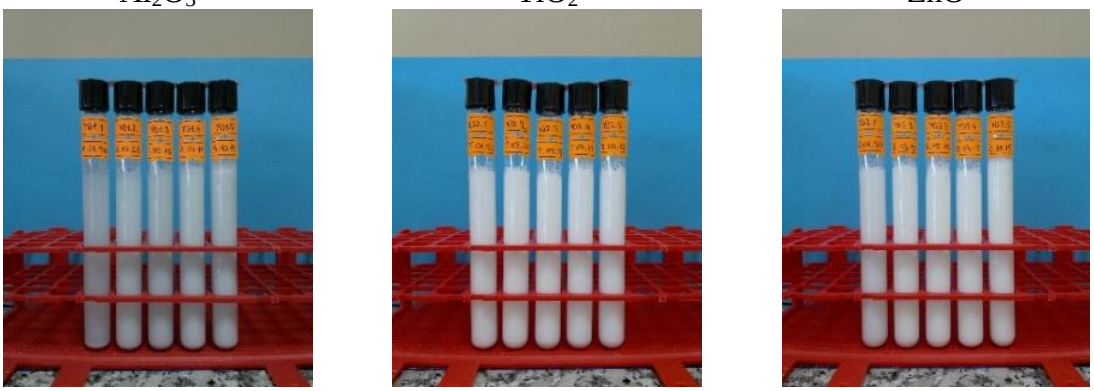


Figure 3. Nanofluids are prepared a various volume concentration

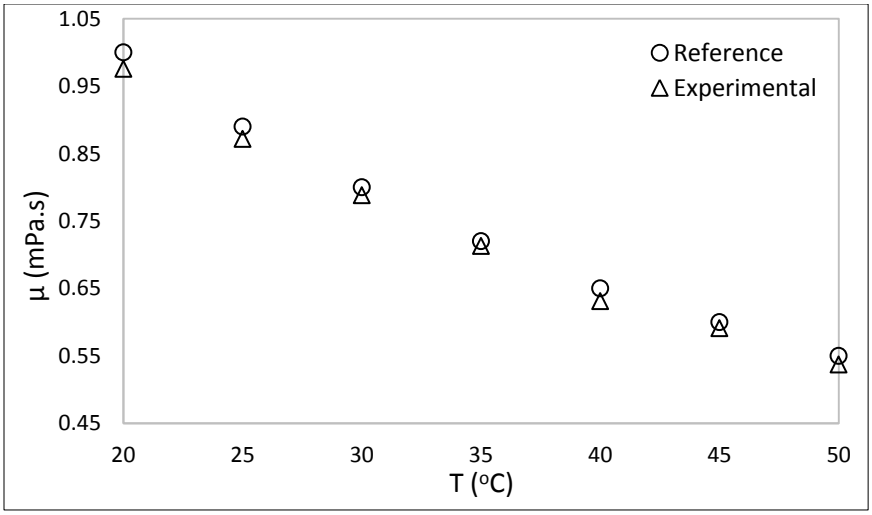
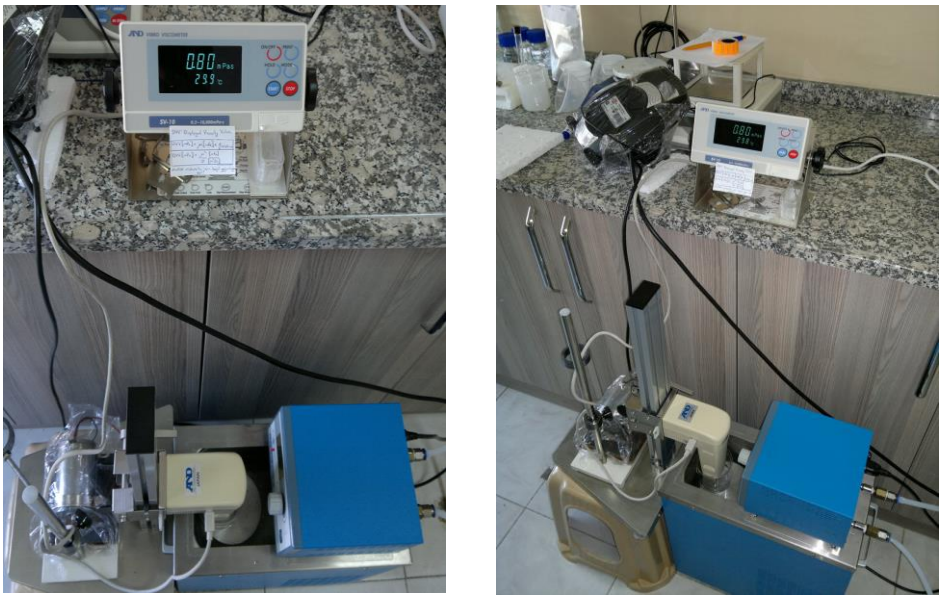


Figure 4. Comparison of experimental viscosity values of pure water with reference values.



(a) (b)

Figure 5. a) Viscometer b) Placement of the viscometer in the heat bath.

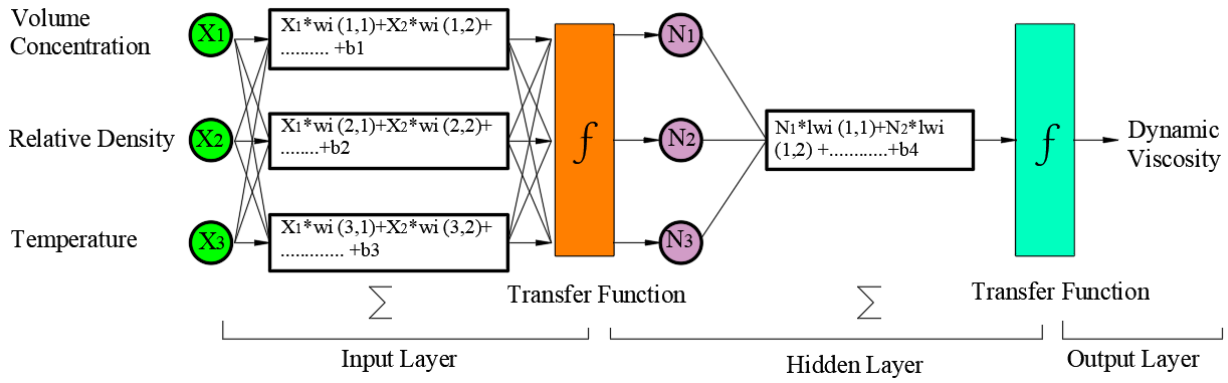
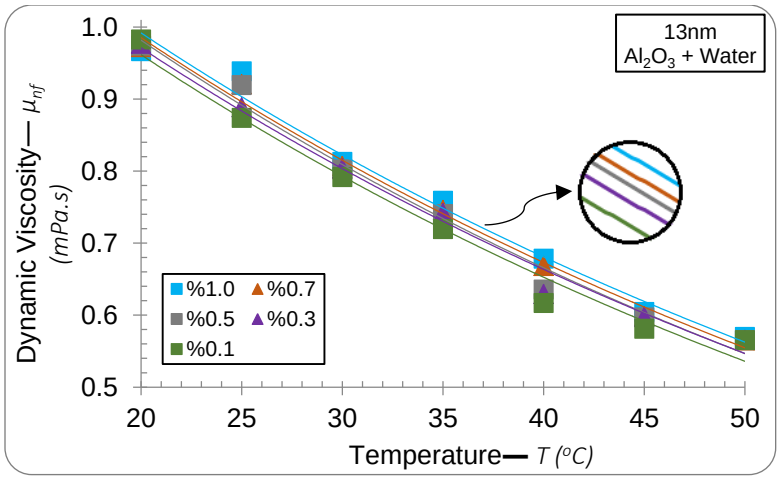
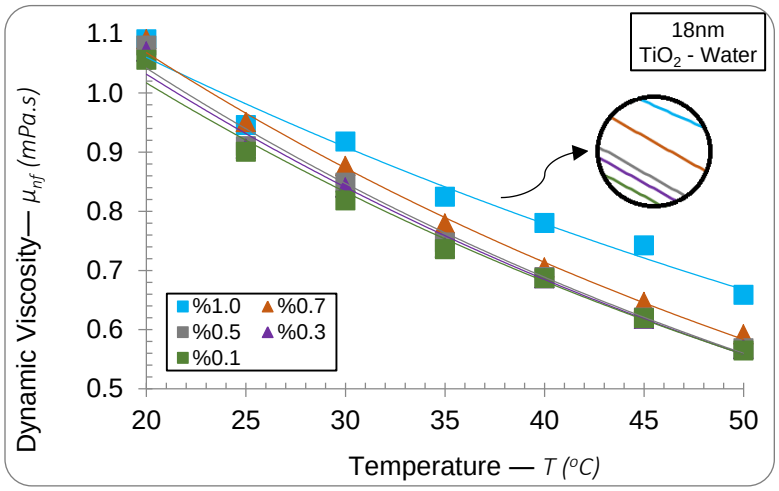


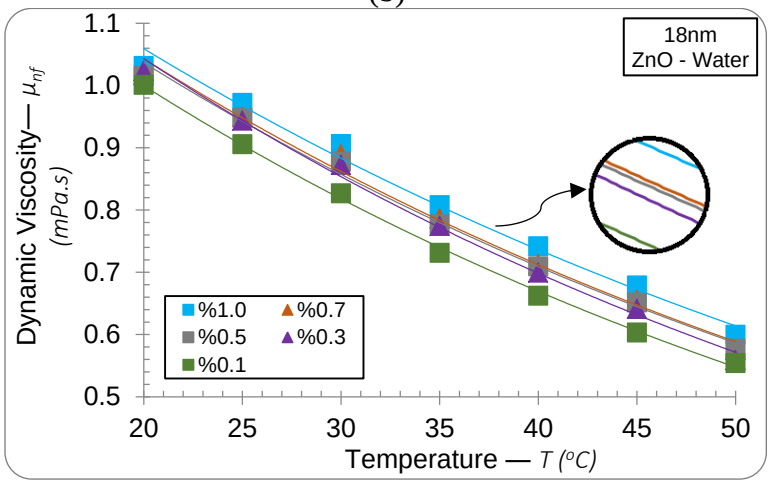
Figure 6. ANN basic elements and the input/output layer of the model.



(a)

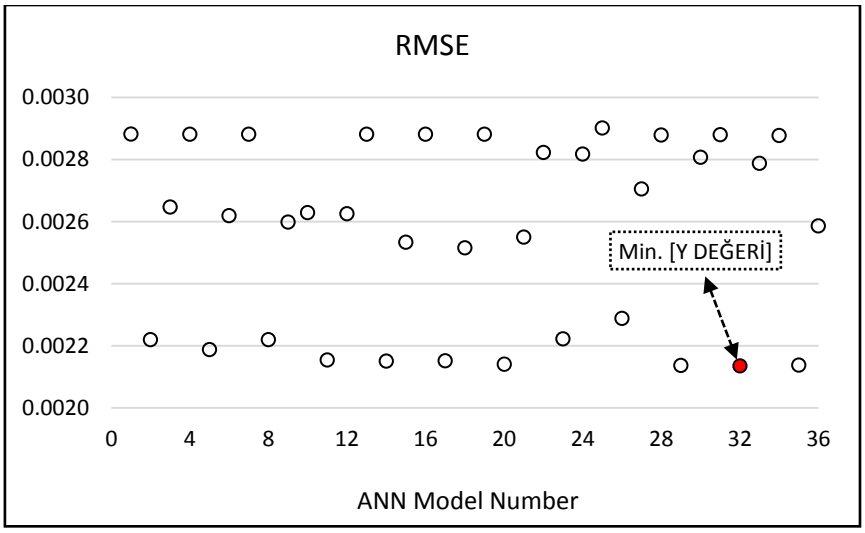


(b)

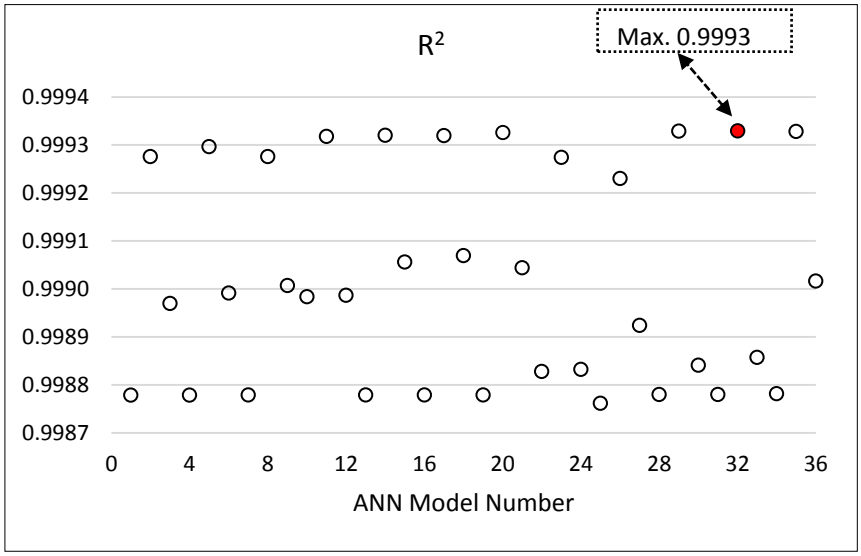


(c)

Figure 7. The variation of dynamic viscosity of Al_2O_3 (a), TiO_2 (b), and ZnO (c) nanofluids as a function of temperature and volume concentration.



(a)



(b)

Figure 8. Variation of RMSE (a) and R^2 (b) at ANN Models for training data.

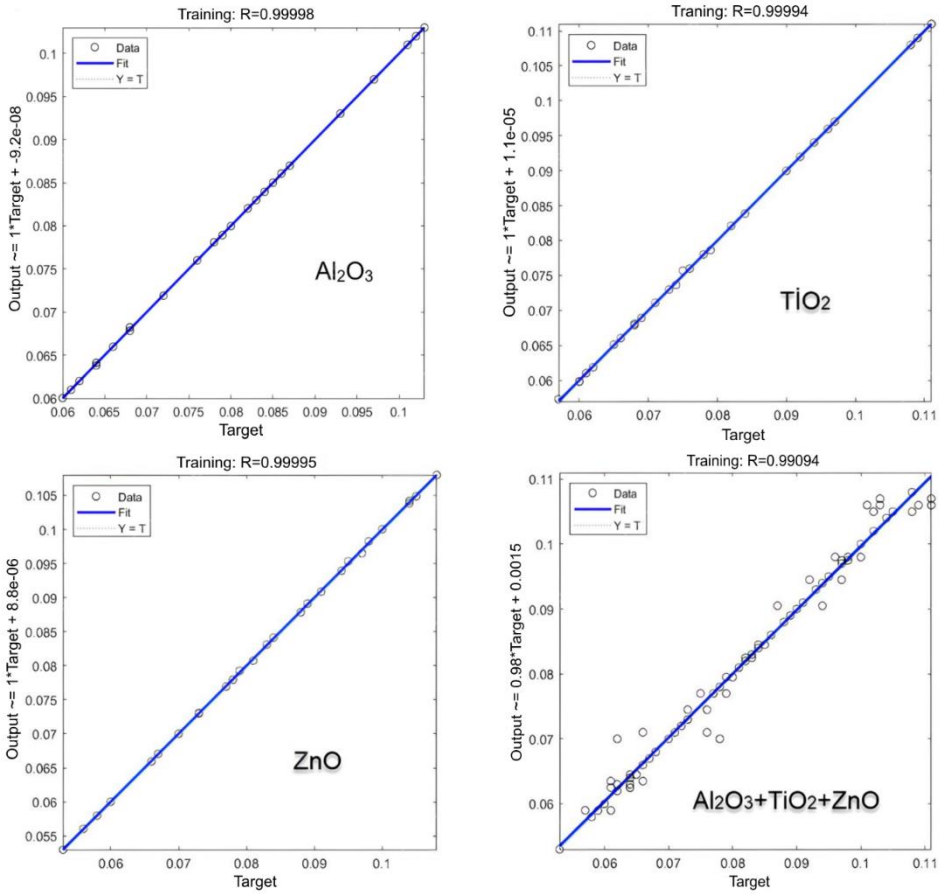


Figure 9. Experimental values vs ANN predicted values for train data.

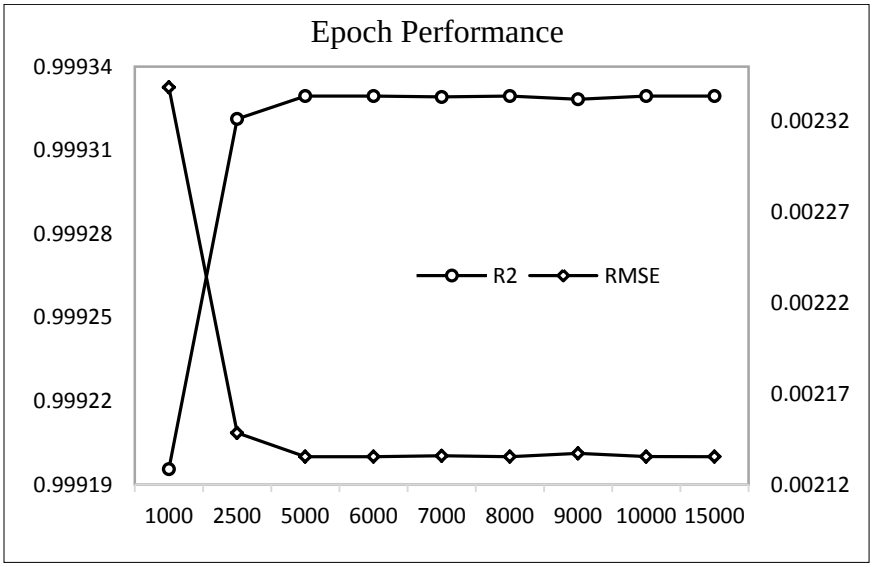


Figure 10. Effect of epoch's number on ANN model performance.

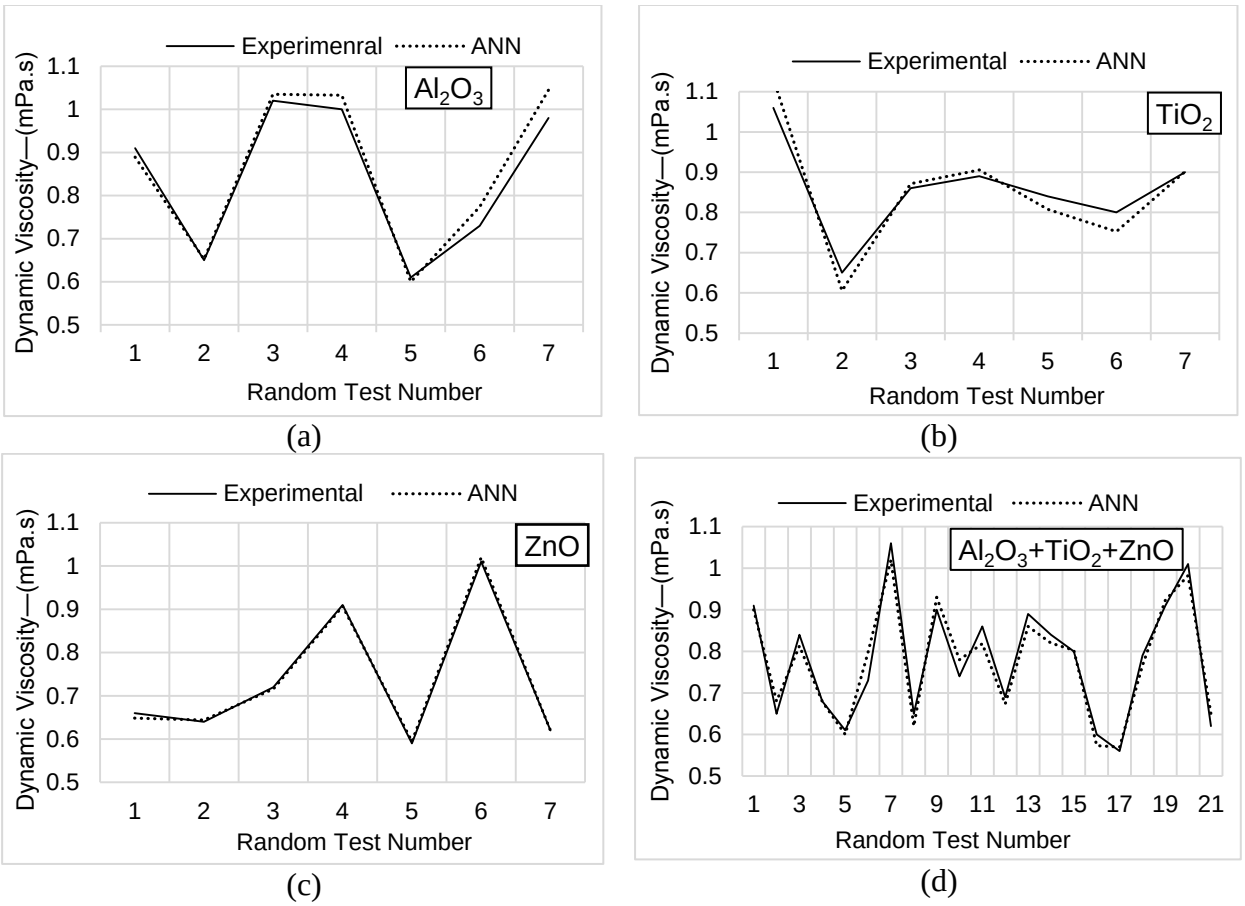


Figure 11. Comparison of experimental and predicted ANN dynamic viscosity of a) Al_2O_3, b) TiO_2, c) ZnO, d) all nanofluids.