

## Artificial Neural Network Technique for Estimating the Thermo-Physical Properties of Water-Alumina Nanofluid

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### ABSTRACT

With its superior thermo-physical characteristics to the carrier fluid, nanofluid is the most impactful heat transfer fluid. Thermal conductivity, density, viscosity, specific heat, coefficient of volumetric expansion, and other thermo-physical parameters play an important part in the thermal management of any heat transfer application. This thermal management governs the service life of an equipment or apparatus, which dissipates heat during its operation. If the equipment is well-managed thermally, then its service life will be extended. Otherwise the equipment stops functioning due to excess heat. Thermo-physical properties of nanofluid vary with the change in the concentration of nanoparticles. Estimation of the properties with the varying concentrations of the nanoparticles is time consuming and is economically not viable. There were many empirical models available in the literature for determining the thermo-physical properties of nanofluids. However, each model provides different values of thermo-physical properties and choosing the best model among the models available is a complex task. In this regard, to avoid the complication in choosing the best model, and in order to envisage the thermo-physical properties of the nanofluid, the Artificial Neural Network (ANN) technique was used. This technique is widely used among the researchers for various applications. The ANN approach was utilized in this work to estimate viscosity and thermal conductivity of water-based  $Al_2O_3$  nanofluid for volume fractions between 0.01% and 0.1%. For thermal conductivity, mean square error (MSE) was observed as  $4.504e^{-09}$  and for viscosity, it was observed as  $6.4742e^{-09}$ . Training times were 5 seconds and 4 seconds for thermal conductivity and viscosity datasets, respectively.

**Keywords:** thermal conductivity, viscosity, heat transfer, nanofluid, ANN.

### INTRODUCTION

Modern electronic devices are to be cooled properly, in order to perform their functions efficiently and for a longer period of time. Higher and efficient thermal management systems render the devices compact, which further leads to the reduction in the weight and cost. Heat transfer can be improved using fans and blowers, jet impingement or even with the help of surface vibration. They are specified as active techniques of intensification of heat transfer and require power sources. Extending the heat transfer surface area improves heat

transfer as well, by adding fins to it and improving the thermo-physical properties of heat transfer liquids without using any external power source. Heat transfer liquids are characterized by lesser thermal conductivity than solids. In order to enhance the thermal conductivity of base fluid, nano sized particles (less than 100 nm) are disseminated in the carrier fluid to form an efficient homogenous heat transfer liquid known as nanofluid.

Nanofluid guarantees enhanced thermal properties and was found to be more useful than the conventional fluids for the applications such as nuclear as well as electronic cooling, automobile

radiators, power transformers etc. It is very much necessary to determine thermal properties like viscosity, specific heat, density, thermal conductivity, volumetric expansion coefficient of the nanofluid before using it in a heat transfer application for calculating the rate of heat transfer. Apart from viscosity and thermal conductivity, other properties of nanofluid are obtained from law of mixtures. Ravi Babu and Sambasivarao [Ravi Babu and Sambasivarao, 2018] established thermo-physical properties for determining the free convective heat transfer coefficient. Experiments were conducted by many researchers to measure the viscosity and thermal conductivity of alumina [Raja Sekhar and Sharma, 2015; Chandrasekar et al., 2010],  $\text{Fe}_2\text{O}_3$  [Syam Sundar and Manoj, 2013], semiconductor [Murshed et al., 2013],  $\text{SiO}_2$  [Abdolbaqi et al., 2016],  $\text{SiC}$  [Li et al. 2016], silicon oil, MWCNT [Bakthavatchalam and Saha, 2020] nanofluids etc. A study on ultrasonic sonication was conducted and optimized time of sonication was found [Mahbubul et al. 2015]. Many literature evaluations on the measurement of rheological parameters and thermal conductivity of nanofluids were undertaken, and the results were presented in a systematic manner [Durgam and Kadam, 2019; Okonkwo et al. 2020; Murshed et al. 2008]. The main drawback of the models developed was that none of the concurrent models suit for all the types and conditions of nanofluids. Therefore, in order to predict the thermo-physical properties, the artificial neural network (ANN) method was used by researchers. Yaswanatha et al. [2020] used ANN for predicting the thermal conductivity of Ethylene Glycol. Sun et al. [2017] used ANN for optics forecasting and Vakili et al. [2016] used ANN for prediction of thermal radiation properties. Wang et al. [2020] used the ANN technique for envisaging the thermal conductivity of ethylene glycol based nanofluids. Mohammad and Davood [2021] suggested a novel correlation for analyzing the relative viscosity of  $\text{Al}_2\text{O}_3$  based engine oil nanofluid using an optimum feed forward ANN model. Humphrey et al. [2020] used ANN based correlation for envisaging thermal conductivity of hybrid nanofluids. Meijuan [2021] reviewed the readings carried out on predicting the thermal conductivity using the ANN technique. He specified in his review that ANN was used for predicting the thermo-physical properties of all types of nanofluids at higher volume fractions. Krishna Varma et al. [2017] carried out experimental

investigations on enhancement of heat transfer in a double pipe heat exchanger using Ferric Oxide Nanofluids. Similarly, many researchers carried out experimental investigations on nanofluids. Some researchers, tried to optimize the process parameters of the nano fluids. Krishna Varma et al. [2018] carried optimized the process parameters of cooling of an engine radiator using Taguchi optimization. Mohan et al. [2017] carried out CFD simulations to analyze the impingement of rectangular jet on a flat plate using nanofluids. It was also found that in the literature, the low volume concentrations of nanofluids provide higher efficiencies and most of the studies on nanofluids were focused on the investigations carried out at low volume concentrations. In the present study, the ANN technique was used to predict viscosity and thermal conductivity of water based  $\text{Al}_2\text{O}_3$  nanofluid at low range of volume fractions i.e., from 0.01% to 0.1%.

## METHODOLOGY

### Preparation of Aluminum Oxide Nanofluids

The synthesis of nanoparticles is finished in the first phase, and dispersion of Nanoparticles in the carrier fluid is completed in the second phase, resulting in a water –  $\text{Al}_2\text{O}_3$  nanofluid. Alumina Nanoparticles were procured from Nano labs, India with 99.5% purity. The average size of the procured nanoparticles was determined using the Scherrer equation, which is shown as eqn. (1) The average size of the nanoparticle was found to be 30–50 nm. Nanoparticles were disseminated in the base fluid in the appropriate proportions based on the known volume concentration of the nanofluid.

$$D = K \lambda / \beta \cos \theta \quad (1)$$

where: K is the Scherrer constant (0.9), D is the nanoparticle diameter, X-ray source wavelength  $\lambda = 0.15406$  nm,  $\theta$  is the peak location in radians and  $\beta$  is the whole width at half maximum from the XRD pattern.

Mass of nano particles required to prepare the required concentration of the nanofluid was determined using the eqn. (2). The quantity of the  $\text{Al}_2\text{O}_3$  nano powder required for the preparation of various concentrations of the nanofluid was as shown in Table 1.

Sodium Dodecyl Sulphate (SDS) of 1/10th of nanoparticle quantity was used as surfactant

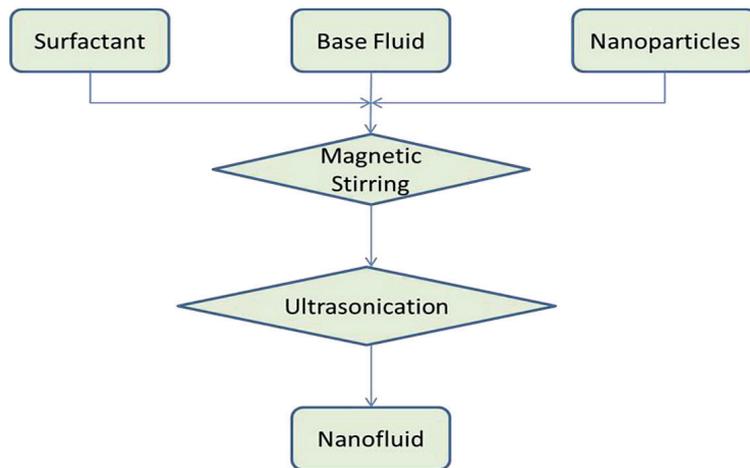


Figure 1. Flowchart of preparation of nanofluid

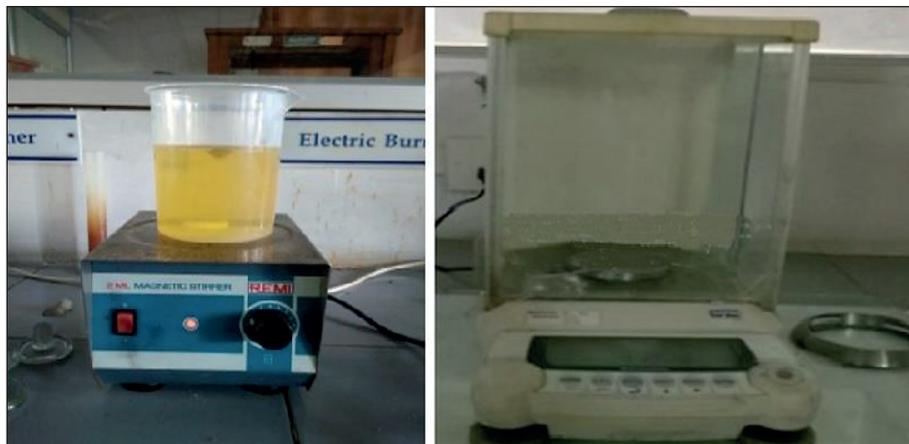


Figure 2. (a) Magnetic stirrer for stirring of nanofluid (b) Digital balance for weighment of nano powder and surfactant

in order to keep the nanoparticles dispersed well without settling. Surfactant usage in excess is not recommended, since it may compromise the thermo-physical characteristics of the nanofluid. Figure 1 depicts a sequential step-by-step method. Initially, the  $Al_2O_3$  nanoparticles and surfactant were measured for the required quantity and were added to the base fluid. Magnetic stirring was carried out for about

half an hour to form a homogeneous solution. After that, the solution was sonicated for about 3 hours using an ultrasonic sonicator (Make: Oscar Electronics) at a frequency of 20 KHz to avoid agglomerations in the nanofluid.

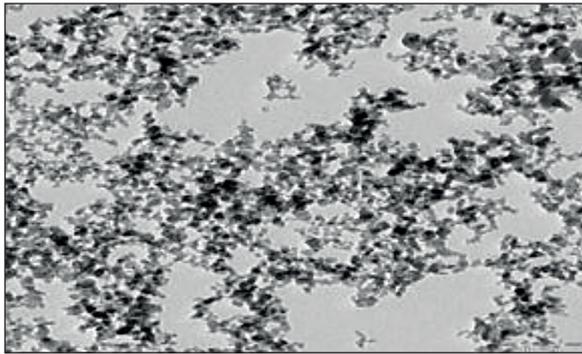
A break of 10 minutes is given in sonication process to prevent the heating of nanofluid

Table 1. Weight of the nano powder required for different concentrations of the nano fluid

Sl. No	Volume concentration (%)	Weight of $Al_2O_3$ nano powder (gm)
1	0.05	1.9869
2	0.1	3.9739
3	0.2	7.9478
4	0.4	15.8956
5	0.6	23.8434



Figure 3. Ultrasonic sonicator



**Figure 4.** Image of Transmission Electron Microscope of water- $\text{Al}_2\text{O}_3$  nanofluid

above the desired temperature. Pictorial view of the magnetic stirrer and the digital balance used for stirring process and for the weighment of the nano powder and surfactant are shown in Figs. 2(a–b), respectively. Figure 3 shows the ultrasonic sonicator.

**Measurement of thermo-physical properties**

Thermal conductivity was evaluated using a KD2 pro thermal analyzer after the water –  $\text{Al}_2\text{O}_3$  nanofluid was prepared, and viscosity was determined using a Brookfield viscometer. In order to ensure accuracy, the devices were calibrated with demineralized water. The experimental data was used to create an ANN model that could predict the thermal conductivity and viscosity of water –  $\text{Al}_2\text{O}_3$  nanofluid.

$$\Phi = \frac{(m_{np}/\rho_{np})}{(m_{np}/\rho_{np}) + (m_{bf}/\rho_{bf})} \quad (2)$$

where:  $\Phi$  is the vol. fraction % of the nanofluid;  $m_{np}$ ,  $m_{bf}$  are masses of nanoparticles (gm) and base fluid respectively;  $\rho_{np}$ ,  $\rho_{bf}$  are the densities of nanoparticles and base fluid ( $\text{kg}/\text{m}^3$ ).

The image obtained from Transmission Electron Microscope (TEM) of water-based  $\text{Al}_2\text{O}_3$  nanofluids is shown in Figure 4. The TEM image clearly depicts that there were no specific agglomerations observed within the range of 100 nm scale.

**Measurement of thermal conductivity and viscosity**

The KD2 Pro thermal property analyzer (Make: Decagon devices, Inc.) was used to measure the thermal conductivity of the created nanofluid, as illustrated in Figure 5a. It is a hand-held equipment with a needle sensor (1.3x60 mm) that may be inserted into the sample test fluid to determine thermal conductivity. For measuring thermal conductivity, this instrument uses transient line hot source method. The nanofluid container was taken ensuring that its dimensions were sufficiently large compared to sensor needle. This measurement was done based on the assumptions like (i) Infinite long heat source (ii) initial temperature is uniform throughout the medium (iii) medium is homogenous and isotropic i.e., thermal conductivity is similar in all directions.

Viscosity of the liquids was measured using various viscometers and rheometers and presented in the past literature. In this work, a digital Brookfield Viscometer (make: Ktek analytics, India) with a spindle speed of 0 to 1000



**Figure 5.** Photographs of (a) Kd2 pro thermal analyzer, (b) Brookfield viscometer

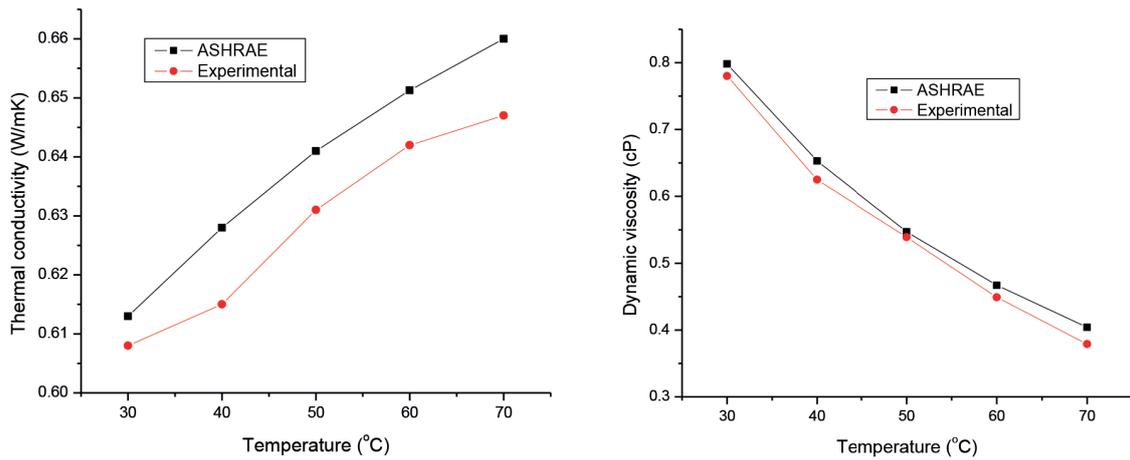


Figure 6. Calibration of (a) KD2 Pro Thermal Analyzer and (b) Brookfield Viscometer

rpm was utilized to measure the viscosity of the nanofluid at varied volume concentrations and temperatures (b). A test sample of 200–400 mL must be deposited in a suitable container and placed beneath the viscometer, which is then adjusted to dip the spindle into the sample up to a predefined immersion mark on the spindle shaft. The dip-in spindle is ideal for evaluating the viscosity of nanofluids in a relative manner. Calibration of KD2 thermal analyzer and Brookfield viscometer is done by taking demineralized water as sample and measured thermal conductivity and viscosities. The measured values are compared using the ASHRAE data and shown in Figure 6. The maximum errors that occurred in calibration of KD2 pro thermal analyzer and Brookfield viscometer were 3.02% and 3.06% respectively.

### DEVELOPMENT OF ANN MODEL

ANN technique was developed based on inspiration from dendrites in complex human brain system. The proposed ANN model was trained using Levenberg–Marquardt algorithm. Thermal conductivity dataset and viscosity dataset were created using the entire experimental data of thermal conductivity and viscosity measurements. The thermal conductivity dataset and the viscosity dataset were made up of the entire experimental data for measuring thermal conductivity and viscosity. The datasets consisted of 100 measurements of thermal conductivity and viscosity at different volume fractions ranging from 0.01 percent to 0.1 percent. In total, 70 measures were utilized for training, 30 for testing, and 100 for validation. The kind of nanofluid (Alumina),

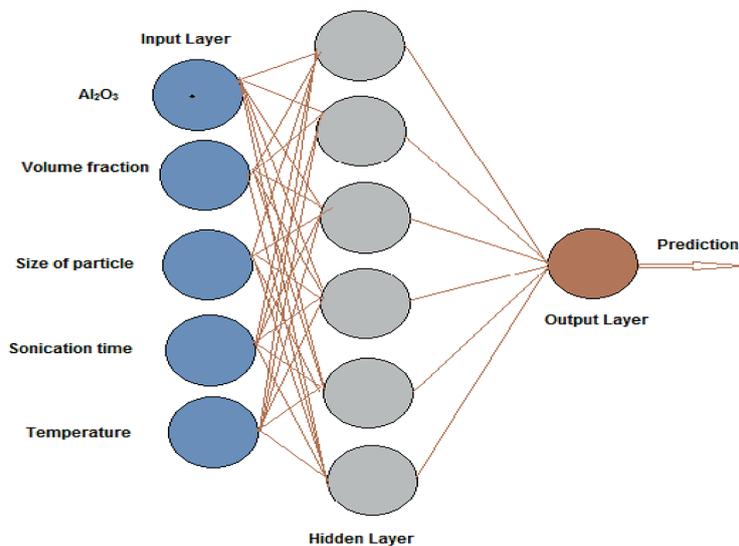


Figure 7. Proposed architecture of ANN

volume fraction, size of the nanoparticle, sonication period, and temperature were all used as input parameters for the ANN model, with thermal conductivity and viscosity as responses. Figure 7 depicts the architecture of the neural network. It is made up of three layers: an input layer with input parameters, a hidden layer with neurons for training, and an output layer that must predict the thermo-physical characteristics of the nanofluid. The model for the current investigation was created using the MATLAB R2019 software. For computing the value of numerous correlation coefficients, the Levenberg–Marquardt method (LM) was chosen (R).

## RESULTS AND DISCUSSIONS

On the basis of experimental data, an artificial neural network model was proposed; 70 percent of the data was used for training, while the remaining 30 percent was used for testing. Validation was carried out by selecting values at random from the data.

### Thermal conductivity model

Neural network training model using thermal conductivity dataset is shown in Figure 8.

In this model, the Levenberg–Marquardt algorithm (LM) is selected for training, data division for validation is used as random, performance of the model is determined by calculating the mean square error and calculations are performed by writing the code in MATLAB. The progress of the learning is observed in Figure 9. Time for training of thermal conductivity dataset is 5 sec. The mean square error value of the model is used to determine the model’s performance. Comparison of training, validation is observed in the Figure 10. The best validation performance is obtained at  $4.5059 \times 10^{-9}$  at epoch number 214. Regression plot for thermal conductivity is observed in Figure 10 in which training data, validation data and all data regressions are presented. Regression coefficient for training data is  $2.6 \times 10^{-7}$ , for validation data it is  $1.3 \times 10^{-5}$ , for all data it is  $3.8 \times 10^{-6}$ . For several regression algorithms in neural networks, a comparison of mean absolute error (MAE), root mean square error (RMSE), mean square error, prediction speed, and training time was made and provided in Table 2.

### Viscosity model

Neural network training model using thermal viscosity dataset is shown in Figure 11. In this model, the Levenberg–Marquardt

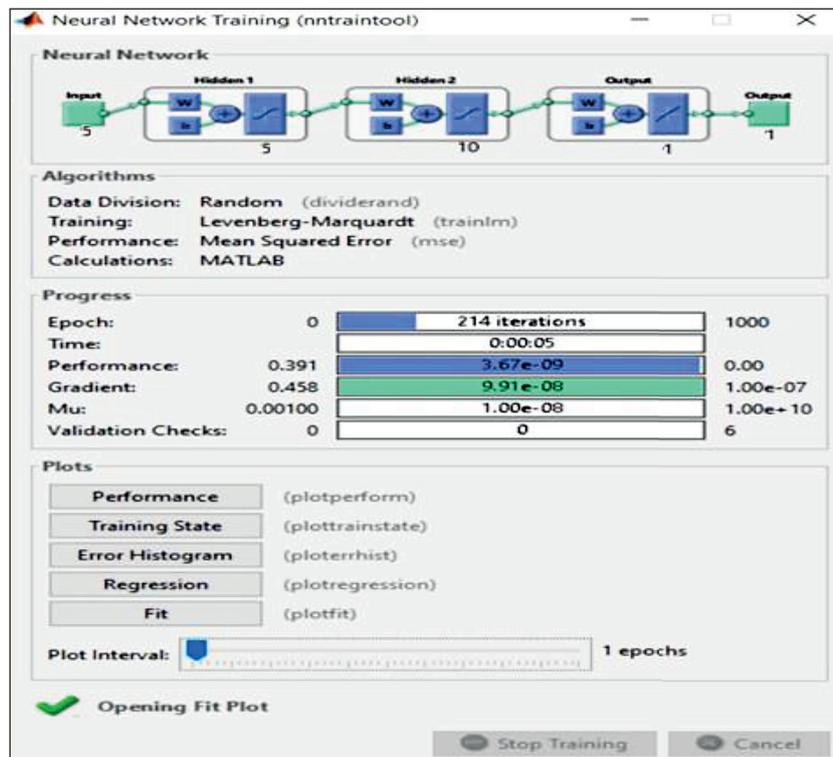


Figure 8. Neural network training using thermal conductivity dataset

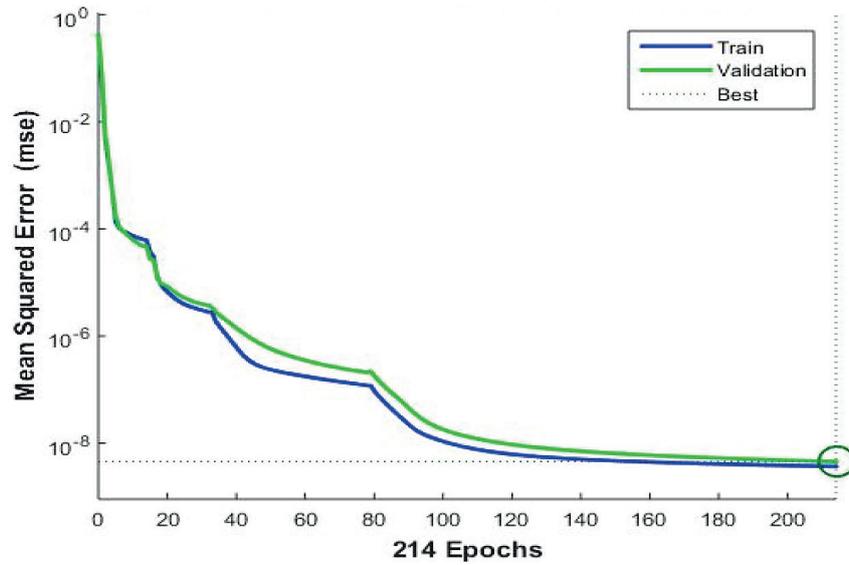


Figure 9. Mean square error of thermal conductivity dataset

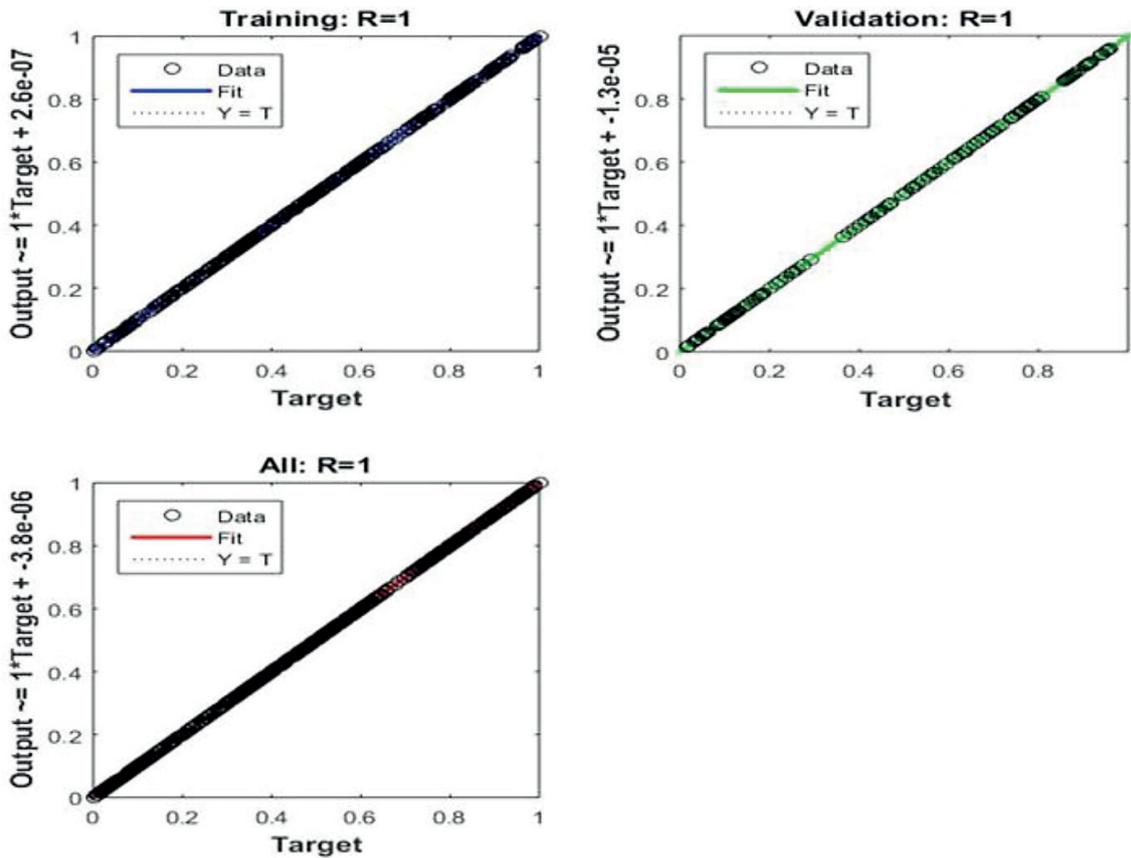


Figure 10. Regression plot for thermal conductivity

Table 2. Comparison of thermal conductivity validation of ANN using different regression methods

Method	RMSE	R <sup>2</sup>	MSE	MAE	Estimation speed (obs/s)	Time of training (s)
Regression tree	0.082347	0.91	0.0065143	0.058212	1500	5.5195
Linear regression	0.080451	1	4.504e <sup>-09</sup>	0.05078	1200	5.0
Gaussian process regression	0.092347	0.85	0.0076158	0.058212	1800	6.5195

algorithm is selected for training, data division for validation is used as random, performance of the model is determined by calculating the mean square error and calculations are performed by writing the code in MATLAB. The progress of the learning is observed in Figure 11. Time for training of thermal conductivity dataset is 4 sec.

The mean square error value of the model is used to determine the model's performance. Figure 12 shows a comparison of training and

validation. The best validation performance is obtained at  $6.4742 \times 10^{-9}$  at epoch number 181.

Regression plot for viscosity is observed in Figure 13 in which training data, validation data and all data regressions are presented. Regression coefficient for training data is  $2.2 \times 10^{-7}$ , for validation data it is  $5.0 \times 10^{-5}$ , for all data it is  $1.4 \times 10^{-6}$ . Comparison of mean absolute error, root mean square error, mean square error, prediction speed and training time is done for various regression methods in neural network is done and presented in Table 3.

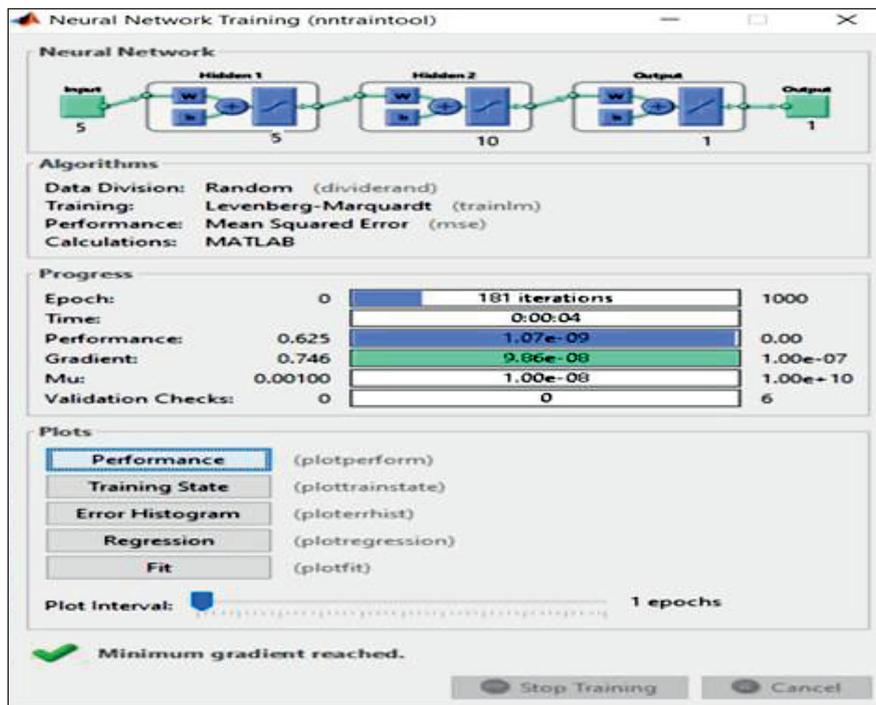


Figure 11. Neural network training using viscosity dataset

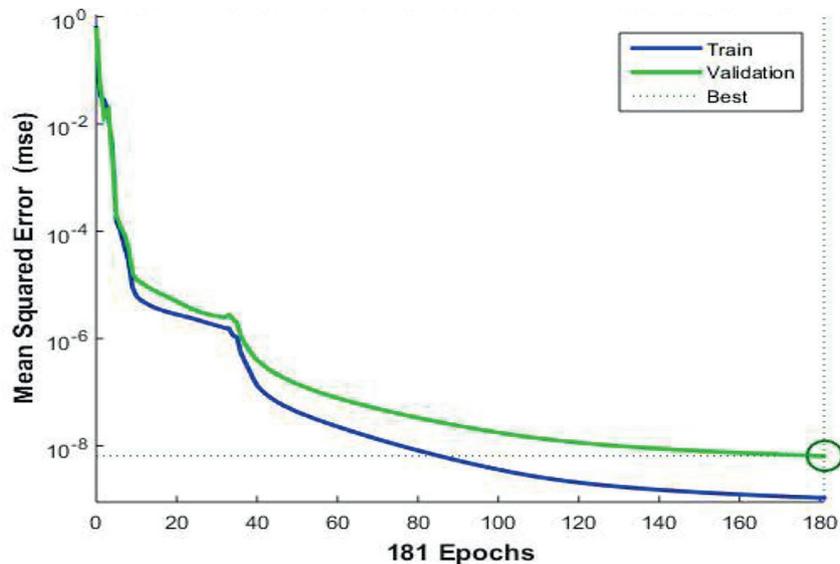


Figure 12. Mean square error of viscosity dataset

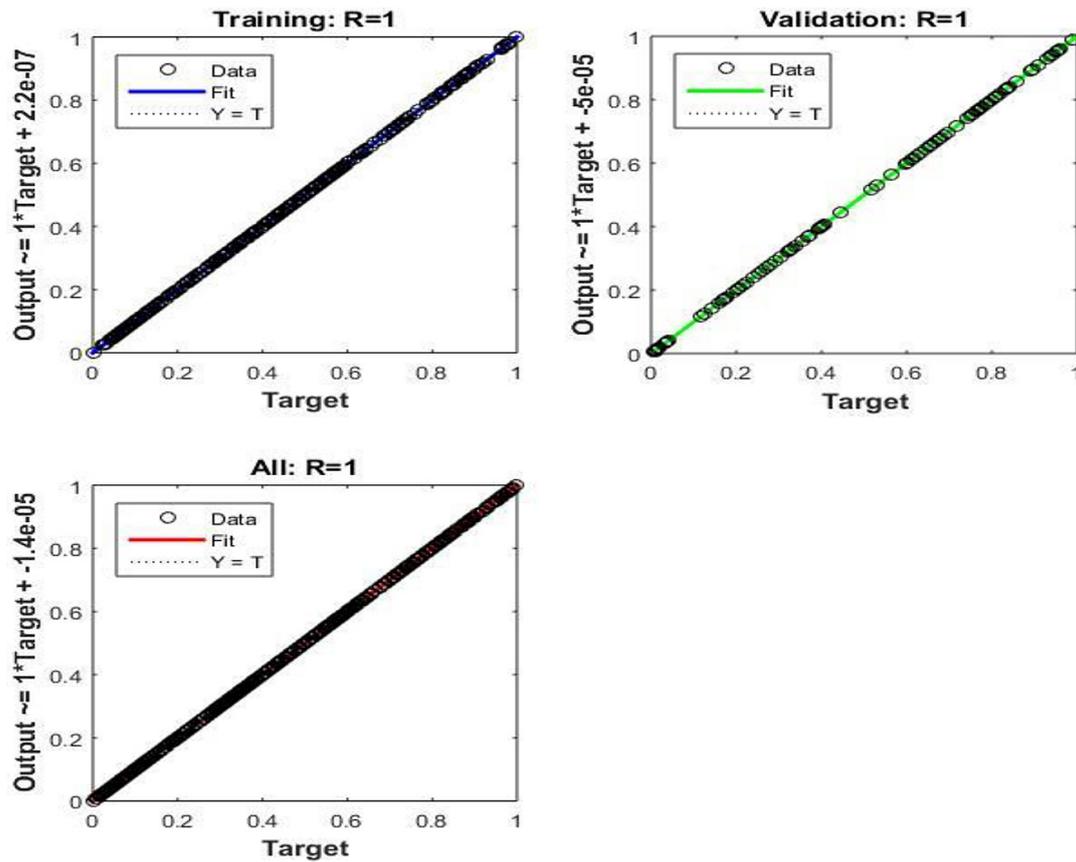


Figure 13. Regression plot for viscosity

Table 3. Comparison of viscosity validation of ANN using different regression methods

Method	RMSE	R <sup>2</sup>	MSE	MAE	Estimation speed (obs/s)	Time of training (s)
Regression tree	0.0072361	0.89	0.006732	0.058212	1400	4.9625
Linear regression	0.0031147	1	6.4742e <sup>-09</sup>	0.002078	1000	4.0
GP regression	0.0072361	0.86	0.006732	0.0687	1600	5.432

## CONCLUSIONS

In this work, the water-alumina nanofluid was prepared for volume fractions between 0.01% and 0.1%. After preparing the nanofluid, the measurement data of viscosity and thermal conductivity of the prepared nanofluid is taken for different volume fractions and this data was used for training the ANN model. In the present study, 70 percent of the data was used for training, while the remaining 30 percent was used for testing. Validation was done by taking the values from data randomly. From the analysis conducted, following outcomes were proposed and presented as follows:

1. For thermal conductivity, mean square error (MSE) was observed as 4.504e<sup>-09</sup> and for viscosity, it was observed as 6.4742e<sup>-09</sup>.

2. For training the datasets of thermal conductivity (K) and viscosity ( $\mu$ ), it took the time of 5 seconds and 4 seconds, respectively.
3. The proposed model was compared for to test the model’s performance using several regression methods and it was observed that linear regression achieved the better performance among other techniques.
4. This method is useful for chemical and mechanical Engineers for selecting the nanofluids and for enhancing the thermal performance of the equipment.

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