

Retraction

Retracted: Evaluation of Physicothermal Properties of Silicone Oil Dispersed with Multiwalled Carbon Nanotubes and Data Prediction Using ANN

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] R. Surakasi, K. C. Sekhar, E. Yanmaz et al., "Evaluation of Physicothermal Properties of Silicone Oil Dispersed with Multiwalled Carbon Nanotubes and Data Prediction Using ANN," *Journal of Nanomaterials*, vol. 2021, Article ID 3444512, 11 pages, 2021.

Research Article

Evaluation of Physicothermal Properties of Silicone Oil Dispersed with Multiwalled Carbon Nanotubes and Data Prediction Using ANN

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The researchers wanted to see whether MWCNTs changed the physicothermal properties of solar thermal working fluids. Assessing thermal properties is vital for solar thermal efficiency. Lubricant contains silicone oil resurfaced. It contains 0.25, 0.5, 0.75, and 1.0% multiwalled carbon nanotubes. Before dispersion in thermic fluids, nanomaterials must be properly surface modified. Between 100°C and 300°C, a fluid's thermal conductivity and specific heat physical characteristics like viscosity and density may be inferred from data collected between 50°C and 150°C. Thermal conductivity increases by 15% to 20% when carbon nanotubes are dispersed. The pressure drop is minimal at 0.5 percent weight fraction, demonstrating the suitability of nanofluids in closed loop systems. The characteristics are forecasted using feed-forward backpropagation method and GRNN, and the best of them is selected for prediction. In this research, hidden layer neurons and factors are examined.

1. Introduction

Nanofluid research relies heavily on the study of thermophysical characteristics, which are the primary determinant of heat transmission and flow behaviour. As is the case with typical solid-liquid suspensions that may support particles as small as millimeters or micrometers in size, several studies show that the average density and specific heat of nanofluids can be estimated using energy conservation as well as mass conservation concepts. Due to variances in preparation technique, measurement methodologies, and data analysis methods, there are few agreements on other critical thermophysical parameters of nanofluids (particularly for thermal conductivity and viscosity). Numerous researchers [1–6] examined the progress on nanofluid thermophysical characteristics from various experimental and theoretical studies.

According to their study, adding nanoparticles to base fluid increased thermal conductivity and viscosity to variable degrees, depending on nanoparticle attributes, temperature, and base fluid. Determining the impact of nanoparticle attributes, base liquid types as well as temperature on overall thermophysical properties of nanoparticles was also based on experimental data. However, as the improved transport characteristics of nanofluids may be impacted by various variables, the present studies have difficulties mostly in prediction for nanofluid thermophysical properties by applying the model-based method. As ANNs have significant nonlinear mapping capabilities, they may describe complex mapping connections amongst input components as well as output targets without the need for accurate mathematical modelling. The usage of ANN in thermal research, including such modelling thermophysical properties and

forecasting heat transfer behaviour, has increased in recent years. Unfortunately, despite the fact that some studies revealed that ANNs were an effective technique for predicting the thermal physical properties of nanoparticles, there were considerable differences in the types of ANNs used and the ANN structures determined. The modelling approach and effectiveness of ANN for predicting nanofluid thermophysical parameters will need to be further investigated to better comprehend this issue. Thermophysical characteristics of carbon nanotubes and silicone oil are being studied in the current study.

CNTs are nanometer-sized carbon tubes. CNTs' atomic bonding and aspect ratios are unique. Carbon nanotubes are 100 times stronger than steel. It has two origins. Covalent bonds provide the initial strength. Many uses are possible because of its unique aspect ratio, strength, and heat conductivity. Carbon-based materials absorb the most sunlight. SWCNTs are produced by wrapping graphene around graphite. CNT nanofluid are also used in solar thermal collectors. This is due to a lack of dispersion in basic fluids. It is difficult to separate because of hydrophobicity and strong interparticle interactions. CNTs produce unstable CNT dispersions. Sadly, previous research was narrowed. There is stability of dispersion in solar thermal collectors. Dispersion of CNTs by ultrasonication or surfactants is possible, but unstable. Use it to create solutions that are stable even when left open. Choosing the appropriate base fluid, CNTs, and dispersants is the initial step. So far, several CNT solutions have not been tested at high temperatures. STCs' UV-VIS-NIR stability was tested. The CNTs are characterized using EDX, HRSEM, and TEM techniques at each stage of the preparation process. Figure 1 shows the simple structure of a carbon nanotube.

The structure of silicone oil is shown in Figure 2. Polymerized siloxane with organic side chains is silicon oil. For their stability and lubricating qualities, they are very commercial. Thermic fluid is the primary benefit of silicone oil. Alternating silicon and oxygen atoms (Si-O). Linear polymers and cyclosiloxanes are common.

Silicone oil is a great lubricant since it is nonreactive and very slippery. Silicone oil is often used because of its distinct chemical structure, unique combination of properties, low viscosity temperature change, and lack of corrosiveness. When it comes to lubricants and hydraulic fluids, silicone oils are a go-to choice because of their versatility. To heat baths in labs, they are often employed because of their excellent heat transmission and stability at a range of temperatures. This source also powers oil-filled heaters and diffusion pumps.

DPDM400 High Temperature Silicone Heat Transfer Fluid has a viscosity of 400 cSt at 25°C. High oxidation resistance, dielectric strength, and hydrophobicity characterize DPDM400 High Temperature Silicone Heat Transfer Fluid (insoluble in water). Its high viscosity-to-temperature coefficient allows it to flow easily.

2. Literature Review

According to Agarwal et al. [7], TC of alumina nanofluids produced from various base liquids were synthesised, char-

acterized, and sensitivity tested. The synthesis combustion solution technique was used to produce the specimens at three different temperatures. They discovered that increasing the combustion temperature increases particle size. It took two steps to scatter alumina nanoparticles of 52 nm size, combusted at 10000°C, in water and ethylene glycol. For water- and EG-based nanofluids, the TC increased by 30% and 31%, respectively, from 10 to 700°C and 0 to 2 volume %. The sensitivity analysis shows that TC variation increases with volume %.

Reddy and Rao [8] investigated ethylene glycol-water mixtures at three different concentrations of nanoparticles. It is possible to create nanofluids by dissolving small amounts of nanoparticles using basic liquids such as water, 40:60 ethylene glycol/water, or 50:50 ethylene glycol/water. They discovered that when nanoparticle volume % and temperature rose, the TC climbed from 30°C to 70°C.

Surakasi et al. [9] have done studies using the basic fluids being monoethylene glycol and water. Nanofluids are administered at concentrations ranging from 100:0 to 90:10 to 80:20. They were mixed with purified and oxidized multiwalled carbon nanotubes in 0.125, 0.25, and 0.5 weight percent weight fractions, respectively.

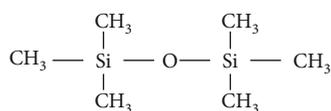
According to Esfe et al. [10], the TC of an alumina-water nanofluid was predicted using an ANN model as well as correlation of experimental data at multiple temperatures and volume percentages. The training data employed in the ANNs is the TC of the nanofluids at several fluid temperatures, extending from 25 to 60°C. Additionally, centred on the experimental data, a correlation for predicting the thermal conductivity of the nanofluid vis-a-vis temperature and volume percentage is suggested. The findings indicate that the suggested correlation could forecast the TC of the nanofluids. Further, the ANN model also showed excellent matching with the findings of the experimentation.

Afrand and Esfe [11] compared empirical-based and ANN-based models for the prediction of experimental of TC of MgO-water nanofluid by using a curve fit model to develop a correlation, and then, the data was forecasted using artificial neural networks (ANNs) with the input variables as volume fraction of MgO and temperature and the output variable as TC. The findings revealed that the network consisting of seven neurons correctly anticipated the outcomes with the least amount of error. Ultimately, a comparison of both models has shown that ANN modelling was more precise than the curve-fit model in forecasting the TC improvement of the nanofluid.

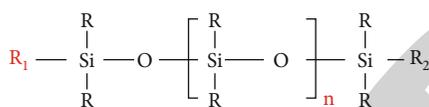
Yousefi et al. [12] established a diffusional neural network structure to model the TC of several nanofluids. They extended the neural network's technique to forecast the relative viscosity of nanofluids suspended with nanosized copper oxide, alumina, titania, and silica. The base liquids selected were propylene glycol-water, ethylene glycol-water, distilled water, and ethanol. The results were compared with other theoretic models as well as experimental values. The projected relative viscosities of dispersions through diffusional neural networks (DNN) are in line with the data found in the literature.



FIGURE 1: Carbon nanotube.



[1] Polydimethylsiloxan



[2] General formula of the silicone oil

FIGURE 2: Structure of silicone oil.

3. Methodology and Experimentation

3.1. Resources. Cheap Tubes Inc. in the United States provided the CVD-produced multiwalled carbon nanotubes used in this research. In the CVD process, manufacturers can combine a metal catalyst (such as iron) with carbon-containing reaction gases (such as hydrogen or carbon monoxide) to form carbon nanotubes on the catalyst inside a high-temperature furnace. The CVD process can be purely catalytic or plasma-supported. MWCNTs have a 20-40 nm diameter, 25-micron length, and 95% purity. Other than that, all of the chemicals I have bought have been of the GR kind. AR grade surfactant was obtained from Sigma-Aldrich India Pvt Ltd. as part of the project. As a hydrocarbon-based thermic, silicone oil is used. Pristine multiwalled carbon nanotubes indicate the presence of impurities like metal particulates and soot entangling CNTs which form agglomerates. The HRSEM image of oxidized CNTs indicates the disentanglement of CNTs due to oxidative treatment with clearly visible open tips. The HRSEM picture of long-length entangled MWCNTs is shown in Figure 3.

3.2. Surface Modification of MWCNTs. A three-step process is implemented (calcination, reflection, and cleaning) for the purification of carbon nanotubes. Pure MWCNTs prefer to

group together when submerged in a liquid. It also causes the MWCNTs to become more entangled, as well as compressing the MWCNTs. To detangle and stabilise MWCNTs in liquid, steric repulsions are created using a surfactant. MWCNTs have a surfactant added to their surface to assist keep them stable in liquid environments. Nonionic surfactant span 80 has a hydrophilic-lipophilic balance of 4.6%. Particle aggregation is inhibited, and surface energy is reduced, modifying ethylene glycol water mixtures with cetrimonium bromide.

To make MWCNTs with changed surfaces, scientists utilise an ultrasonic bath with a surfactant and MWCNTs in it. The MWCNTs get coated as a result of this reaction.

3.3. Preparation of Nanofluids. The 0.125, 0.25, 0.5, and 1 weight percent surface-modified MWCNTs are disseminated in silicone oil mixtures by processing them for approximately 30 minutes in a probe ultrasonicator. The nanoparticle dispersion in liquid coolant up to some proportions is acceptable, since the thermophysical properties could alter with higher proportions. Besides, the issue with nanoparticle stability can be encountered at higher proportions of nanoparticles or nanomaterials that would lead to increased pumping power due to increased viscosity. Hence, the nanoparticle percentage was limited up to 0.5%. Light scattering methods and a zeta sizer are used to assess the stability of thermic fluids distributed with MWCNTs (Horiba SZ 100). A measure of MWCNT dispersion stability in liquid media was measured using the zeta potential.

4. Physicochemical Property Evaluation

4.1. Thermal Conductivity. The major reason for developing nanofluids was to boost a fluid's thermal conductivity by adding nanoparticles to the mixture. Recent decades have seen a great deal of research into the nanofluids thermal conductivity utilising a number of methodologies including the transient hot-wire method as well as the temperature oscillation approach [13]. Nanofluids were shown to

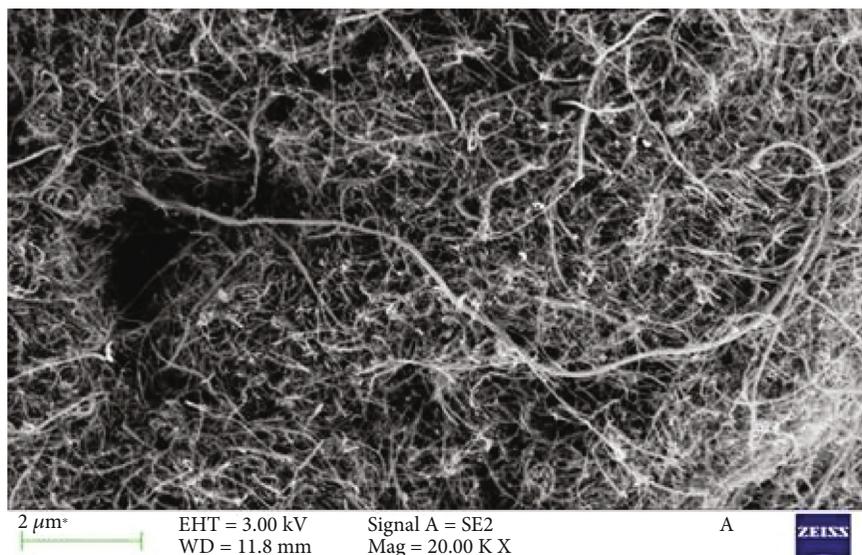


FIGURE 3: HRSEM images of pristine MWCNTs.

improve heat conductivity to variable degrees in most of the studies that were conducted. Nanofluid thermal conductivity may increase due to a variety of macroscopic variables, including decentralised processing techniques, the fundamental characteristics of nanoparticles and base fluids, and temperature. A Hot Disk™ Heat analyzer TPS 500 measures the discs' thermal conductivity. A study is being conducted on the thermal conductivity of fluids containing MWCNTs.

4.2. Dynamic Viscosity. The viscosity of a fluid is a property that indicates its resistance to flow. It is a word that refers to a fluid's internal friction. Viscosity, another critical thermophysical parameter, describes the internal flow resistance of nanofluids. Viscosity affects cranking power as well as heat transfer rate in industrial settings. To better understand the rheological properties of nanofluids, further research on the effect of nanoparticles on base fluid viscosity is needed. Carbon nanotube-containing nanofluid viscosity is being investigated experimentally at various CNT mass percentages and temperatures, as previously reported. The viscosity of liquids and nanofluids is determined using an absolute viscosity viscometer, such as the Wells-Brookfield C&P. A cone and plate viscometer are used to precisely measure torque over a range of rotating speeds. When determining the rotational resistance of a sample fluid, the torque measurement instrument employs a beryllium-copper spring calibrated to the fluid's specific gravity.

4.3. Artificial Neural Networks. Humans have used artificial neural networks (ANN) to solve problems in fields including health, economics, and engineering. Like the human brain, ANNs may learn patterns from input data before predicting output. That is not all it can do. It is an all-round tool to model and simulate scientific data. It may be used for pattern recognition and nonlinear prediction. It is possible to model and forecast nanofluid thermophysical characteristics using a variety of approaches, the most common of which are theoretical model-based, empirical correlation-

based, or data-driven. The ANN's superior modelling, non-linear mapping, and recognition capabilities have drawn substantial attention in the recent years when compared to the other two techniques [14]. ANN was constructed based mainly on feed-forward back propagation algorithm and TRAINLM training function in which the weights of all neurons are tuned for predicted and measured outputs.

ANN models are comprise of feed-forward, recurrent neural networks, "hybrid neural networks," "radial basis function," "multilayer perceptron," "probabilistic neural networks," "generalized regression neural network," and "reformulated neural networks."

As a rule, a neural network consists of three layers: input, hidden, and output. They recommend adding hidden layers to improve accuracy of neural networks. The input neurons feed the buried layer of ANNs. The "hidden layer" moves data from one layer to another. When an input is given, synapses outline the result. Synapses are flexible components that make up a system. The hidden layer's number of neurons is adjusted from 2 to 6. MATLAB learns the experimental values by comparing input and output values. With silicone oil's volume percent, MWCNT mass fraction, temperature taken as input values and TC and viscosity are taken as output values.

4.4. Back Propagation Method. It is also known as backward propagation in supervised learning using gradient descent. This is called "backward error propagation." It is a common way of calculating a network's loss function's slope. Reweighting neural networks based on errors are called backpropagation. Correct weight adjustment reduces errors and increases model consistency. This method produces the error gradient function given the ANN values and the weights of neural networks.

To train a neural network, backpropagation is used to fine tune the weights (iteration). Weight modification minimises error and improves model reliability.

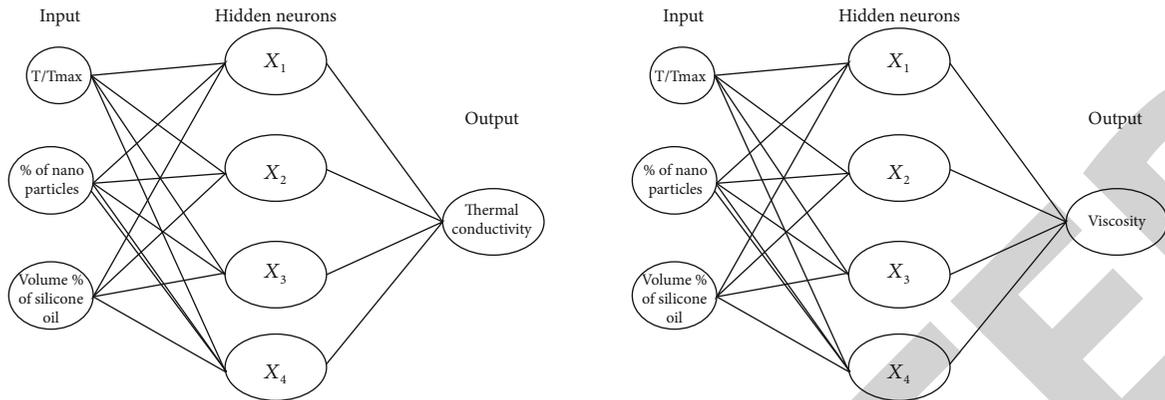


FIGURE 4: Backpropagation method for prediction of thermal conductivity and viscosity.

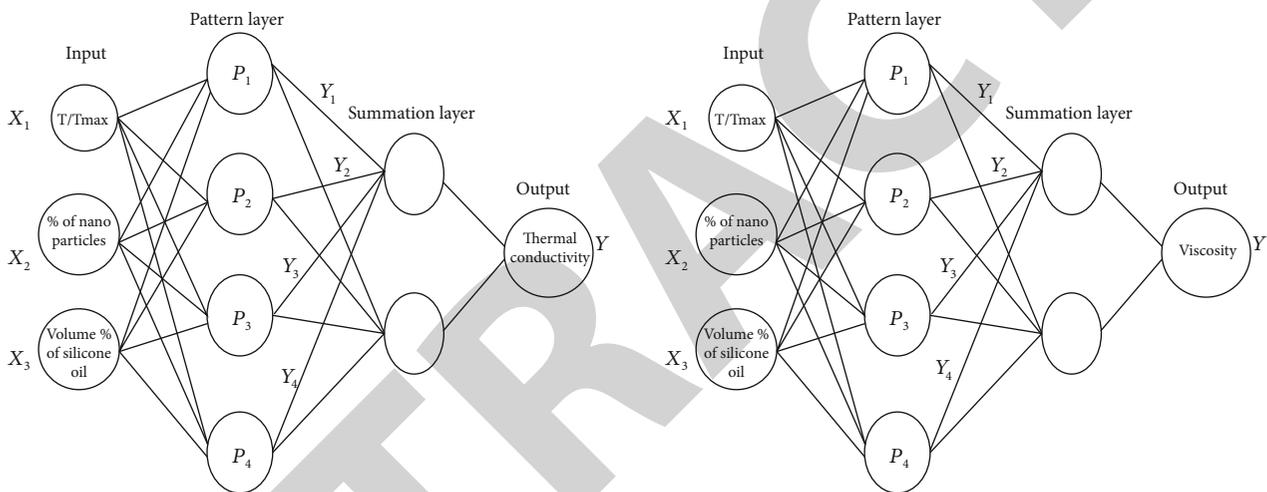


FIGURE 5: Generalized regression neural network function method for prediction of thermal conductivity and viscosity.

4.5. Working of Backpropagation Method. Inputs are sent to the hidden layer. Actual weights W are chosen to model input. Each hidden layer neuron computes output from the input layer to the output layer. Calculate the output prediction error. In case of high error detection, the model uses the hidden layer to return signals from the output to the input layer, reducing the error. Iterate until the required output is achieved with little error.

$$\text{Error } B = \text{actual output} - \text{desired output}. \quad (1)$$

The typically employed activation functions are “Linear,” “Step,” “Sigmoid,” “TanH,” and “rectified linear unit” (ReLU). Figure 4 shows the structure of backpropagation method for prediction of thermal conductivity and viscosity. An ANN model with three inputs, two outputs, and 10 hidden neurons was constructed. Thermal conductivity and viscosity are calculated using temperature, MWCNT percentage, and silicone oil volume percent. To train the ANN, all neuron weights were modified for expected and measured outputs. Performance-wise, we selected pure lin-

ear and tangent sigmoid activation functions. The parameter R^2 predicts the performance of ANNs. R^2 compares the experimental and anticipated values. It improves evaluation precision. It computes the observed and expected results.

4.6. Generalized Regression Neural Network Function. It has 4 layers: input, pattern, summation, and output. GRNN is a variant on radial basis neural networks. The first layer is made up of input vectors. This layer’s outputs are sent to the summation units of the third layer, which have pattern units. The output units are covered by the final layer. Figure 5 depicts the system’s architecture. GRNN uses Parzen’s nonparametric estimator to estimate the probability density function instead of the nonlinear activation function often employed in ANN. Basically, the projected value is a weighted sum of the expected values of training sets that are similar to the input pattern. The only parameter that may be changed is the smoothing factor, which represents the RBF’s width. The function `newgrnn` in Matlab generates GRNN, a parallel distributed radial basis network model. GRNN model performance was impacted by the number

of input vectors and the smooth factor (σ) of the RBF. The GRNN model's input vectors were derived from the main component scores. There were anything from one to ten primary components. RBF's regularisation parameter, the smooth factor, acts as a regularizer. Smoothing the predicted density with a high smoothing parameter causes it to become multivariate Gaussian, with covariance 2, in the limit. The estimated density may take on non-Gaussian forms with a lower value, but there is a risk that wild points will have an excessive impact on the estimate.

5. Discussion and Findings

5.1. Nanofluid Stability. When the zeta potential value is less than 40, it means the system is stable. Higher zeta potential values are found when surface-modified MWCNTs are dispersed in liquid samples. Table 1 displays the outcomes of the experiment.

Thus, poor stability may be inferred from the low zeta potential with pure MWCNTs. Because of this, surface modified MWCNTs have the greatest stability. This is because surfactant exhibits steric repellent forces, which reduce agglomeration rates.

5.2. Thermal Conductivity of Silica Nanofluids. Figure 6 shows that dispersion of nanomaterials improves thermal conductivity. The base fluids, mass fraction, and temperature all play a function in improving thermal conductivity. The thermal conductivity of silicone oil-MWCNT mixes improved more than that of ethylene glycol-water combinations.

5.3. Dynamic Viscosity of Silica Nanofluids. Figure 7 shows the changes in viscosity of several test fluids over time. Viscosity increases considerably as temperature decreases, as shown in the graph below. Higher temperatures, on the other hand, only cause a little rise in viscosity. Since a smaller mass percentage of CNTs is employed in the production of nanofluids, the rise in viscosity is reduced.

6. Prediction of Data Using ANN

6.1. Backpropagation Method. Counting hidden neurons is presently a guessing game. Many studies proposed different ways to distribute ANN hidden neurons. These are pruning techniques. Begin with a modest network (a few neurons); then add hidden neurons. The oversized network is initially pruned to find the smallest size. This study increases the number of hidden layer neurons from 2 to 6. Figure 8 compares ANN-projected dynamic viscosity to experimental values. Here are some graphs showing how many hidden layer neurons affect the error or network. The optimum neuron count is 4. The correlation coefficient falls as the number of hidden layer neurons rises.

The results of values of thermal conductivity forecasted using ANNs are plotted against experimental values as shown in Figure 9. The influence of "number of hidden layer neurons" on the error or the network is shown in the following figures. According to the findings, the hidden layers have no influence on the network's ability to predict values even

TABLE 1: Zeta potential of silicone oil dispersed with MWCNTs.

Sample	Zeta potential (mV)
Silicone oil + 1%pristine MWCNTs	13.8
Silicone oil + 1%surface modified MWCNTs	54.2

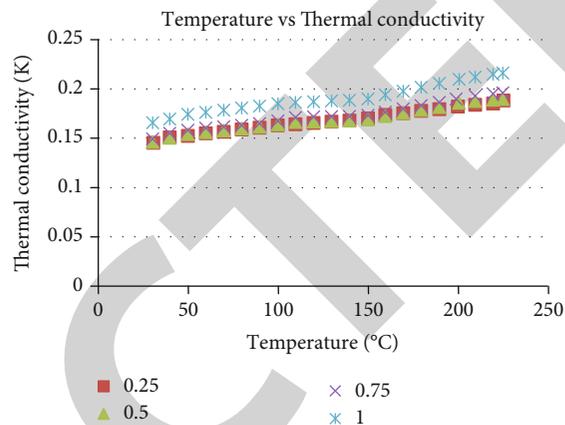


FIGURE 6: Graph indicates the relation between temperature and thermal conductivity at different % of volume fraction.

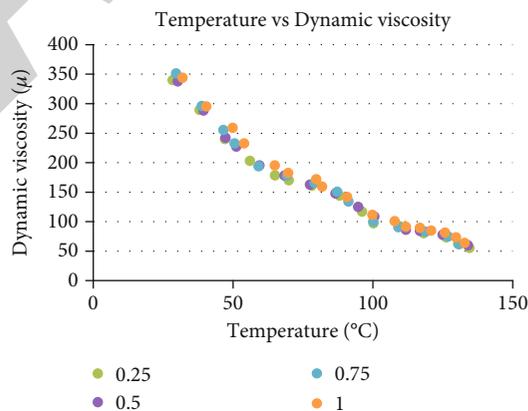


FIGURE 7: Graph indicates the relation between temperature and dynamic viscosity at different % of volume fraction.

when the network has just two hidden layer neurons at the most. This suggests the accuracy of experimentation.

6.2. GRNN Method. Figure 10 compares ANN-projected dynamic viscosity to experimental values. Here are some graphs showing how many hidden layer neurons affect the error or network. The optimum neuron count is 4. The correlation coefficient falls as the number of hidden layer neurons rises.

Figure 11 compares ANN-projected thermal conductivity to experimental values. Here are some graphs showing how many hidden layer neurons affect the error or network. The optimum neuron count is 4. The correlation coefficient falls as the number of hidden layer neurons rises.

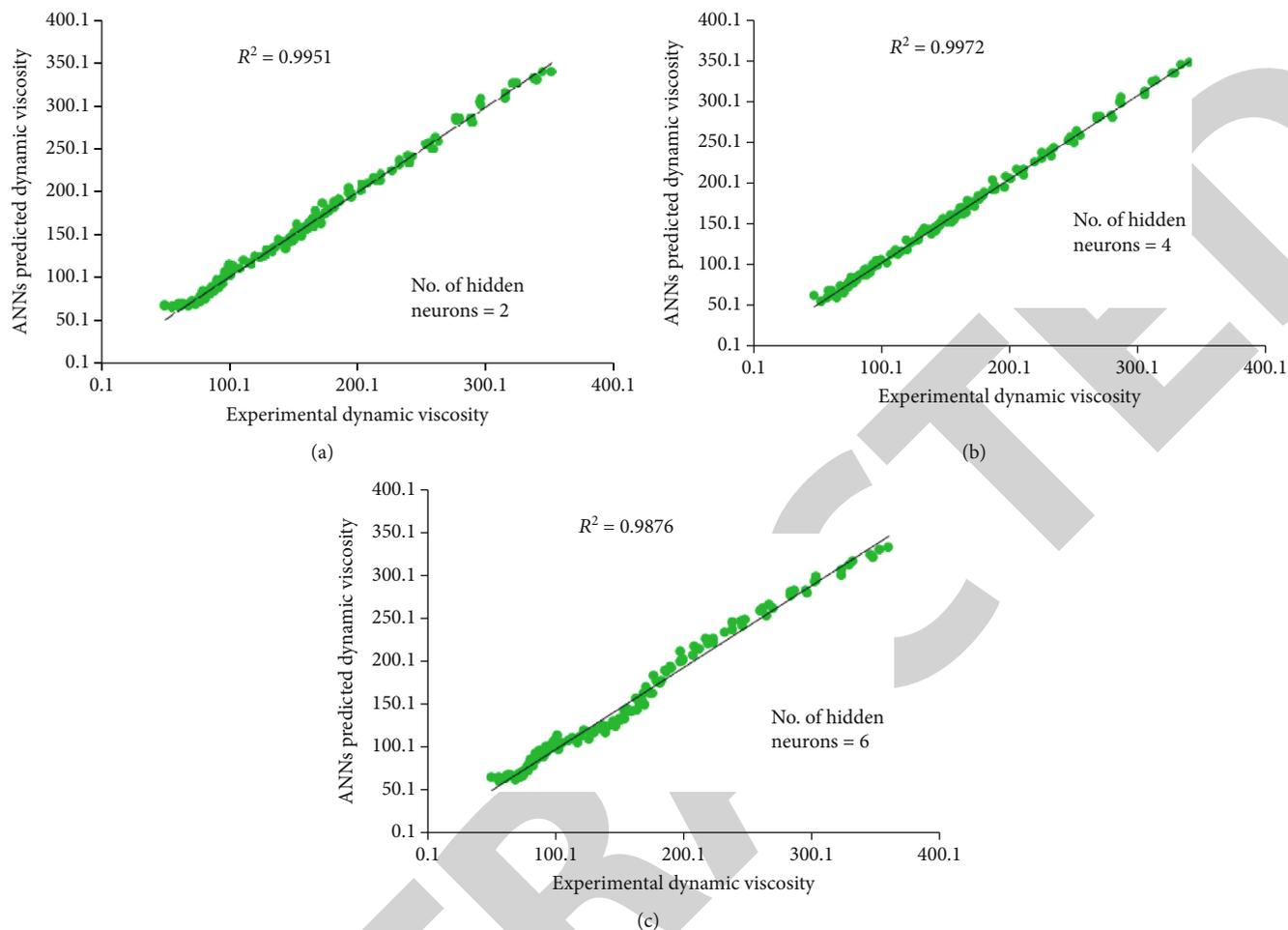


FIGURE 8: Validation of dynamic viscosity data for silicone oil based fluids with varying hidden layer neurons (a) 2 neurons, (b) 4 neurons, and (c) 6 neurons.

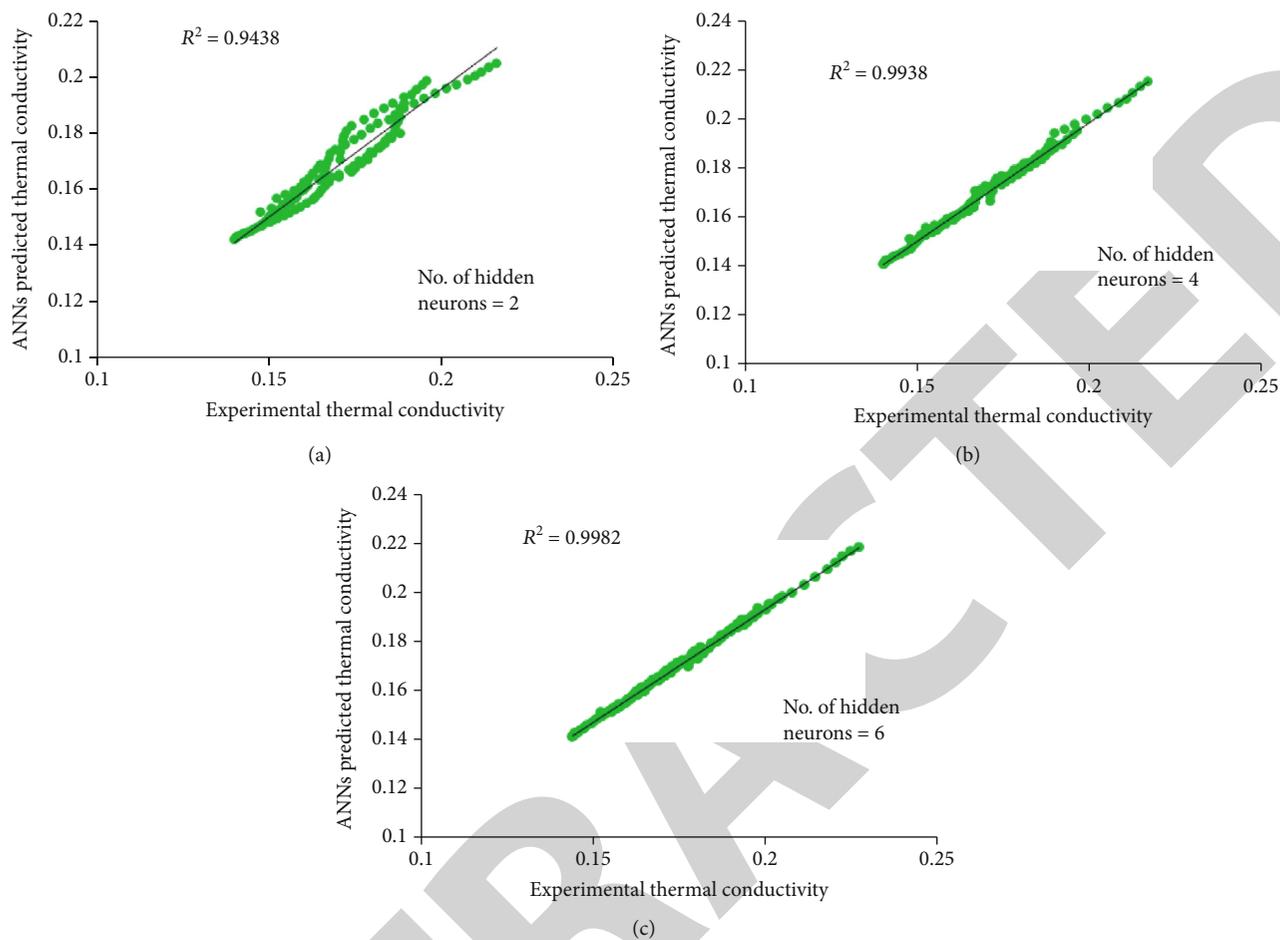


FIGURE 9: Validation of thermal conductivity data for silicone oil based fluids with varying hidden layer neurons (a), 2 neurons, (b) 4 neurons, and (c) 6 neurons.

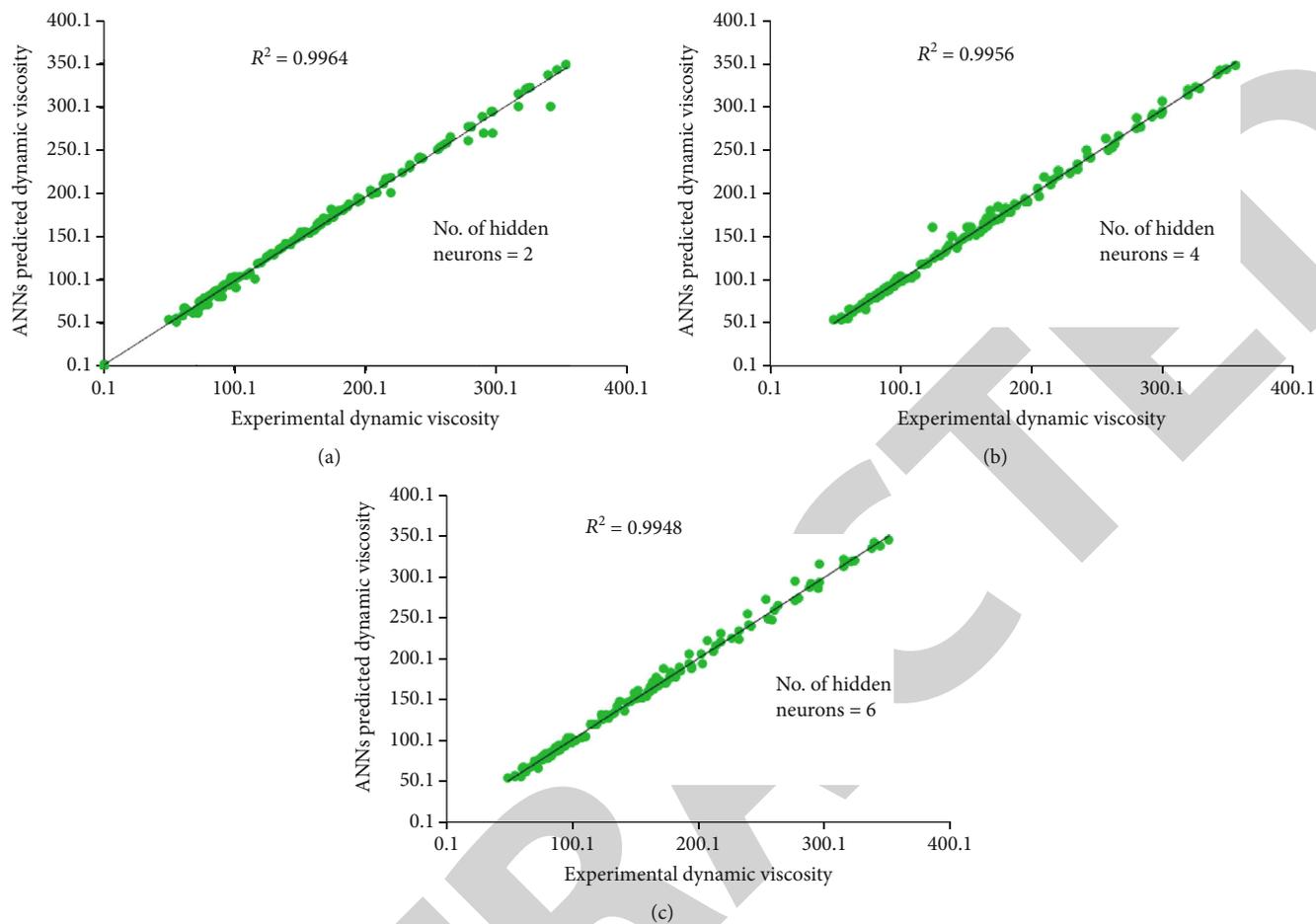


FIGURE 10: Validation of dynamic viscosity data for silicone oil based fluids with varying hidden layer neurons (a), 2 neurons, (b) 4 neurons, and (c) 6 neurons.

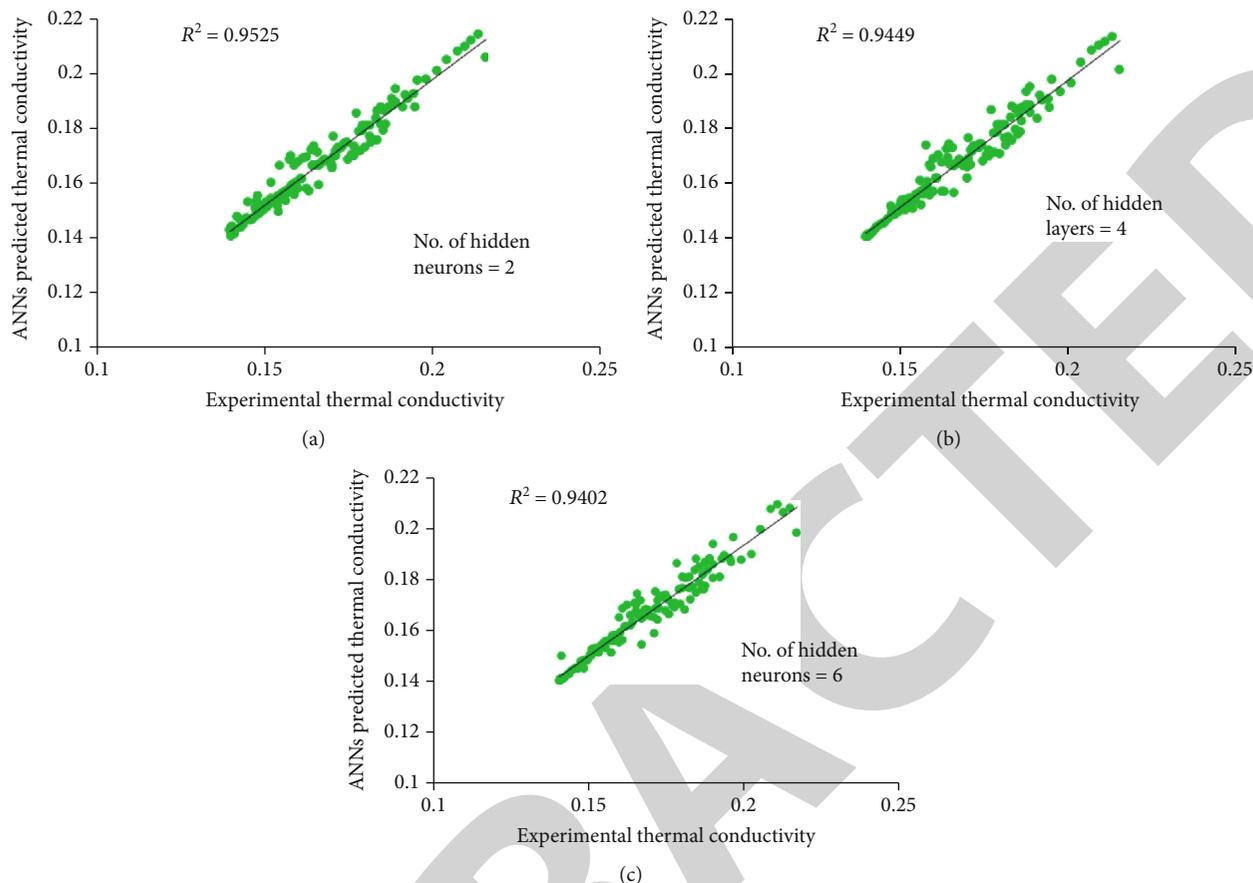


FIGURE 11: Validation of thermal conductivity data for silicone oil based fluids with varying hidden layer neurons (a), 2 neurons, (b) 4 neurons, and (c) 6 neurons.

7. Conclusions

From the results, it can be concluded that the dispersion of MWCNTs in thermic fluids improves the thermal properties. The thermal conductivity increased as the mass fraction increased, and the rise was in the range of 5 percent to 20 percent. There is no variation for viscosity values. The data of thermal conductivity as well as dynamic viscosity can be predicted accurately using artificial neural networks. Prediction of data is done using two methods of ANN that is the backpropagation method and GRNN out of which the value of R^2 for dynamic viscosity is maximum for backpropagation method at number of hidden layers at 4. The value of R^2 for thermal conductivity is maximum for backpropagation method at number of hidden layers is equal to 6. Out of both, the methods for the prediction of the data backpropagation method are found to be the most suitable method compared to other methods, and the back propagation method was given good correlation between experimental and ANN predicted values. The correlation coefficient (R^2) was attained better and improved the accuracy of predictions using back propagation technique. Thus, the back propagation technique was chosen (fixed) for prediction even though other methods were also used. The value of correlation coefficient is found to be declining if the number of hidden layers is increased above 6.

Data Availability

The data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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