

Modeling and optimization of thermal conductivity and viscosity of water-based hybrid nanofluids containing graphene oxide combined with silicon dioxide (Go-SiO₂, 50:50) using MLP & GA

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ABSTRACT

In this study, architecture and training of two artificial neural networks (ANNs) were designed to predict the thermal conductivity (TC) and viscosity properties of nanofluids GO-SiO₂ (50:50, Graphene Oxide and Silicon Dioxide)-based nanofluids. The nanofluid samples investigated comprised various weight fractions (0.1–1%) of a 50:50 mass-ratio mixture of graphene oxide (GO) and silicon dioxide (SiO₂) nanoparticles dispersed in the base fluid; their viscosity and thermal conductivity were measured at temperatures ranging from 30 to 60°C. For each ANN developed to predict either nanofluid viscosity or TC, the regression plots corresponding to the training, validation, and test datasets provided a clear demonstration of the network's optimal performance. Specifically, the mean and maximum relative errors obtained for the test dataset were 0.3425% and 0.8359%, respectively, for viscosity prediction, and 0.2465% and 0.4069%, respectively, for TC prediction. Furthermore, following a sensitivity analysis of the networks, we found that the weight fraction exerts a more pronounced influence on nanofluid viscosity and TC than temperature. Subsequently, a genetic algorithm (GA) applied to the trained ANN models identified the optimal conditions as a weight fraction in the range of 0.1–1% and a temperature of 60°C.

KEYWORDS: Hybrid nanofluids; Weight fraction; Artificial neural network; Optimization; Genetic algorithm

1- Introduction

Water-based hybrid nanofluids containing graphene oxide (GO) combined with silicon dioxide (SiO₂) are colloidal suspensions in which GO nanosheets and SiO₂ nanoparticles are simultaneously dispersed in de-ionized water. The GO-SiO₂ architecture is usually achieved by growing SiO₂ nanospheres onto the GO surface, yielding a covalently bonded hybrid that hinders the restacking of GO and the aggregation of SiO₂ [1]. The GO-SiO₂ couple is attractive because GO contributes exceptionally high intrinsic TC and surface area, while hydrophilic SiO₂ decreases the

overall density, improves chemical robustness, and mitigates the increasing viscosity penalty that normally accompanies high-aspect-ratio carbon nanostructures [2]. Traditional factorial or one-factor-at-a-time optimization methods are local, laborious, and ignore coupled effects; hybrid artificial neural network-genetic algorithm (ANN-GA) frameworks overcome these limitations by combining the predictive power of machine learning (ML) with the global search capability of evolutionary computation, enabling multi-objective optimization of nanofluid to be achieved within minutes instead of hours [3].

Shahsavari et al. [4] presented a study on a novel optimization/statistical approach known as the Robust Weighted Least Squares Support Vector Regression (RWLS-SVR) algorithm. This algorithm was deployed to estimate the thermal properties of a hybrid nanofluid composed of water, Graphene Oxide, and Silicon Carbide. The paper outlined the methodology, which integrates concepts from support vector machines (SVM) to enhance accuracy by minimizing the influence of outliers while maintaining computational efficiency. Experimental results were evaluated across varying temperatures and nanoparticle volume fractions to validate the effectiveness of the proposed method. Ansari Mahyari et al. [5] discussed the experimental investigation and formulation related to the thermal conductivity (TC) of a hybrid nanofluid consisting of water, graphene oxide, and silicon carbide nanoparticles. The study outlined the preparation, stabilization, and measurement of thermal properties, highlighting the increases in TC with variations in temperature and nanoparticle concentration. The authors utilized scanning electron microscopy (SEM) and X-ray diffraction (XRD) for structural analysis and conducted thorough assessments, finding that the TC significantly improved at higher concentrations and temperatures. Kazemi et al. [6] investigated the rheological behavior of mono and hybrid nanofluids using graphene and silica nanoparticles, specifically examining their effects on the viscosity of water across various concentrations and temperatures. They reported the experimental findings that revealed non-Newtonian pseudoplastic behavior for nanofluids, with the hybrid nanofluid demonstrating characteristics between those of the mono-nanofluids. The study also provided correlations to estimate the rheological behavior of the hybrid nanofluids and highlighted the importance of these properties in improving heat transfer applications. Nguyen et al. [7] emphasized the significance of graphene oxide in various applications, such as hydrogen storage and energy conversion. The research investigates the TC of the nanofluid, reporting a notable enhancement of 26.93% in TC at specific volume fractions and temperature ranges. The study also included the use of XRD, dynamic light scattering analysis, and SEM to assess the properties of the nanoparticles. A new numerical correlation for TC was developed, achieving a high accuracy in predictions through ANN modeling. Nazir Ahmad et al. [8] discussed a study on the rheological behavior of a graphene oxide/silica composite aimed at reducing industrial costs. The

volume fractions of the composite ranged from 0.1% to 1.0%, and tests were conducted across various shear rates and temperatures. Characterization techniques such as XRD and field emission SEM were utilized. The investigation revealed non-Newtonian behavior in viscosity measurements, followed by the development of a correlation and the training of an ANN model. The model demonstrated significant accuracy with low tolerances for shear rates examined, suggesting the nanofluid's potential for industrial applications. Rashidi et al. [9] presented a comprehensive review of the thermal performance of hybrid nanofluids, emphasizing the importance of their thermophysical properties—TC, specific heat, and dynamic viscosity—in energy conversion systems. The study highlighted that these properties are significantly influenced by factors such as the volume fraction of solids, the size of solid particles, and temperature. The authors noted that increased volume fractions enhance TC and dynamic viscosity, while specific heat variation depends on the base fluid. The paper also acknowledged the effectiveness of various modeling approaches, particularly intelligent algorithms like ANN, in accurately predicting these thermophysical characteristics. Huminic et al. [10] discussed the development of a new hybrid nanofluid composed of graphene oxide sheets and silicon nanoparticles for thermal applications. They emphasized the excellent properties of graphene oxide, such as high TC, and the effects of varying the mixture ratios on the dynamic viscosity of the nanofluid when dispersed in distilled water. Experimental results demonstrated that viscosity increases with the ratio of graphene oxide, leading to a proposed correlation for dynamic viscosity based on these findings. Kumar Kanti et al. [2] investigated the TC and viscosity of water-based nanofluids that contain silicon dioxide, graphene oxide, titanium dioxide, and their hybrids across varying concentrations (0 to 1 vol%) and temperatures (30 to 60°C). The findings indicated that hybrid nanofluids exhibit superior thermal performance compared to base fluid water, with graphene oxide nanofluids showing significant enhancements in TC (52% at 60°C) and viscosity (177% at 30°C). Advanced ML models, particularly the Random Forest model, were utilized to model these thermophysical properties, revealing crucial insights about the role of temperature and concentration on TC and viscosity predictions. Snoussi et al. [11] presented a study on the dynamic viscosity of nanofluids, which are used in radiative heat transfer engineering. The research emphasized the challenges of measuring dynamic

viscosity and the limitations of existing theoretical and empirical correlations. To overcome these issues, the authors applied various artificial intelligence (AI) techniques, particularly ML, using experimental datasets from 30 sources involving seven different nanoparticles and eight base fluids. They developed a deep learning model that outperformed other established algorithms, achieving a determination coefficient (R^2) of 0.9892 and a root mean square error (RMSE) of 0.0086. Razzaq et al. [3] focused on the significance of nanofluids. The review outlined how the integration of nanoparticles enhances TC, convective heat transfer rates, and the viscosity of these fluids. They elaborated on the consequential benefits for various engineering applications such as heat exchangers, electronics cooling, and renewable energy technologies. The authors discussed mechanisms that contribute to these enhancements, such as nanolayer formation and Brownian motion, while also addressing the environmental impacts, including potential toxicity and sustainability challenges.

The principal objective of the present study is to develop and train two feed-forward, two-layer artificial neural networks (ANNs) using benchmark experimental data available in Kanti et al. [2] to predict the viscosity and thermal conductivity (TC) of GO–SiO₂ (50:50 graphene oxide and silicon dioxide)-based nanofluids. The trained models enable accurate estimation of these thermo-physical properties for arbitrary nanoparticle concentrations in the base fluid and any desired fluid temperature. Subsequently, a genetic algorithm (GA) is coupled with the ANN models to determine the optimal

nanoparticle concentration and temperature, simultaneously minimizing viscosity and maximizing TC. A relevant literature survey reveals that a few previous investigations have employed ANNs combined with GA to estimate the rheological and thermal parameters of nanofluids—especially for the GO–SiO₂ hybrid nanofluid addressed here. This study aims to fill this research gap and to shed light on possibly lesser-known facts about the aforementioned issues.

2- ANN Structure and Modeling

To develop predictive models for the viscosity and TC of GO–SiO₂ (50:50 graphene oxide and silicon dioxide)-based nanofluids, two separate feedforward ANNs—each with a hidden layer containing three neurons—were configured and initialized for training using MATLAB. As illustrated in Fig. 1, each network is tasked with establishing a functional relationship between the input features—nanofluid temperature and nanoparticle weight fraction—and the target output, i.e., either viscosity or TC. For each output quantity, 60% of experimental data points were assigned for training, 20% for training validation, and the remaining 20% for testing the respective network. Additionally, the Levenberg–Marquardt optimization algorithm was employed to train the networks via error back-propagation, thereby updating the weight and bias states, while the mean-squared-error (MSE) between the network outputs and the target values served as the performance index, as defined in Eq. (1).

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (1)$$

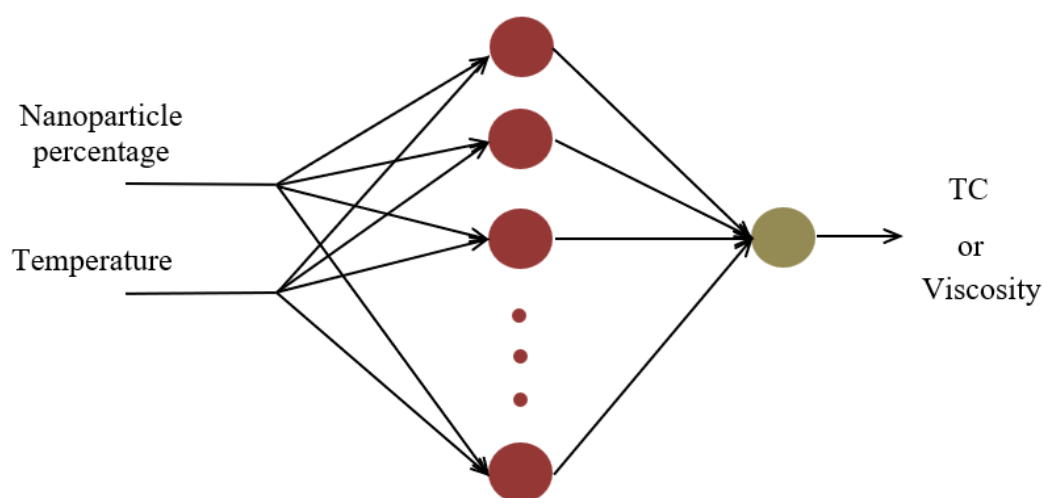


Fig. 1: Architecture of the two-layer backpropagation ANN for TC and viscosity prediction

where n denotes the number of experimental data points, Y_i is the measured (actual) output, and $\hat{Y}_i$ is the corresponding ANN-predicted value for the i -th sample. To enhance network performance, all input and output variables collected from the experiments were normalized to the range $[0, 1]$ before processing. The transfer functions selected for the hidden and output layers are the tangent-sigmoid and linear functions, respectively. Training termination was triggered when the number of successive validation-performance failures reached 10.

One of the most critical indicators of the training trajectory of an ANN is its performance curve, which traces the evolution of the mean-squared error (MSE) throughout the training process. This curve is displayed for the networks tasked with predicting nanofluid viscosity and TC in Figs. 2-3, respectively. In each figure, a monotonic downward trend in the MSE is evident for the training, validation, and test data, signifying stable and favourable convergence. The minimum validation MSE achieved during training is highlighted by a green circle; the corresponding values are 7.8977×10^{-5} at epoch 25 for the viscosity network and 2.5580×10^{-6} at epoch 25 for the TC network. Globally, the lowest overall MSEs recorded across the entire dataset are 5.3727×10^{-5} for the viscosity-predicting ANN and 3.6365×10^{-5} for the TC-predicting ANN.

Regression plots and correlation coefficients

(R) between the actual network outputs and the target values for the trained networks predicting nanofluid viscosity and TC are presented in Figs. 4-5, respectively. For the viscosity network (Fig. 4), the R for the training, validation, test, and entire datasets are 0.99978, 0.99981, 0.99977, and 0.99973, respectively. Similarly, for the TC network (Fig. 5), the corresponding values are 0.99975, 0.99999, 0.99942, and 0.99974. All R values are very close to the ideal value of unity, indicating that the developed neural network models can predict the viscosity and TC of nanofluids containing various weight percentages of the studied nanoparticles at different temperatures with high accuracy.

Figs. 6-7 present the error histograms, displaying the frequency (count) of residuals across varying error margins for the viscosity and TC networks, respectively. In these bar charts, a brown vertical line marks the zero-error position; the closer the majority of bins are to this line—and the higher their frequencies near zero—the greater the model's accuracy. The bulk of high-frequency bins cluster tightly around the zero-error line, corroborating the appropriateness of the training strategy and the overall reliability of the obtained results.

The fitting profiles and relative percentag error (the ratio of the difference between actual and predicted values to the actual value) plots for the trained networks predicting nanofluid viscosity and TC are

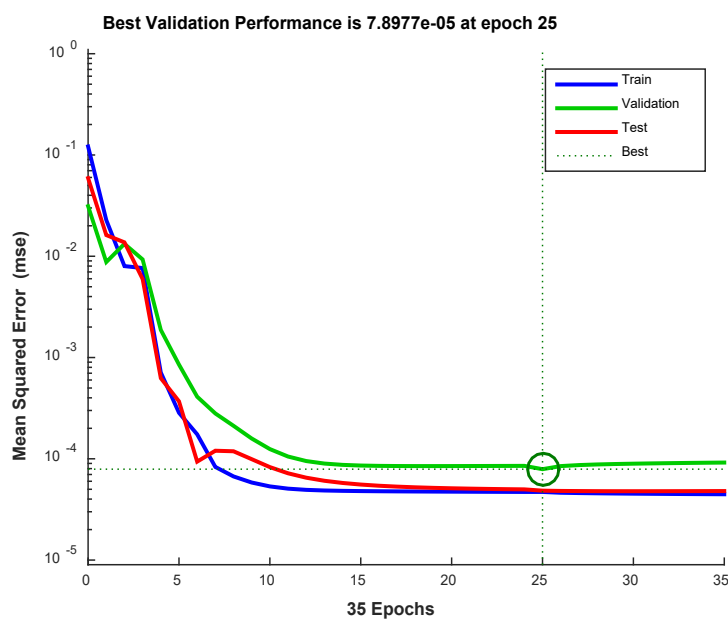


Fig. 2: ANN performance profile showing the evolution of the MSE metric during optimization for the training, validation, and test subsets of the nanofluid viscosity dataset

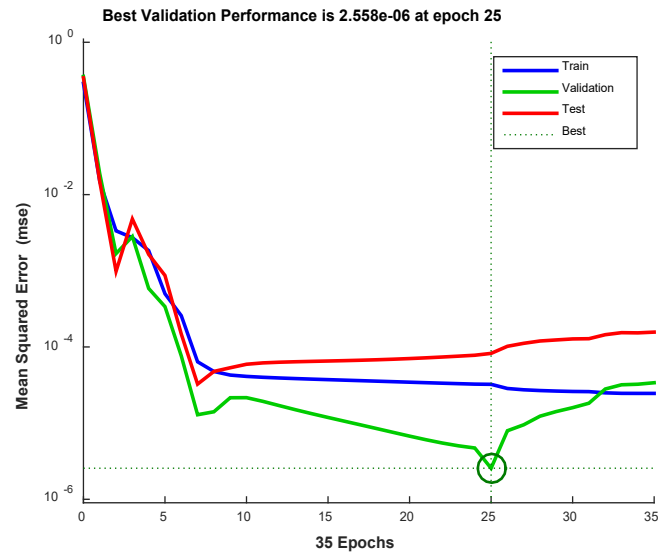


Fig. 3: ANN performance profile exhibiting the evolution of the MSE metric during optimization for the training, validation, and test subsets of the TC dataset

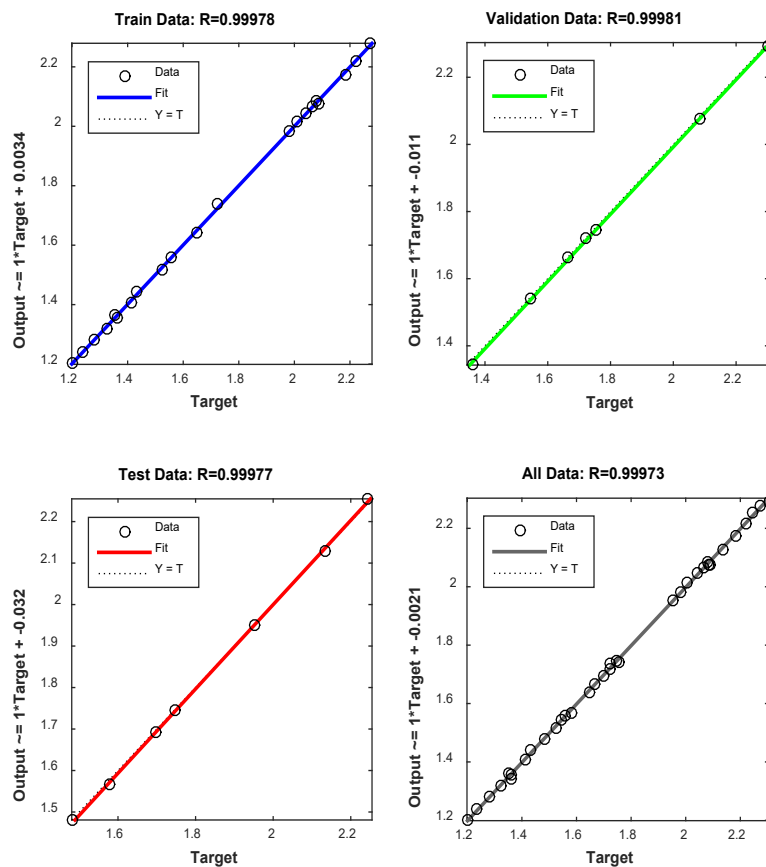


Fig. 4: Regression plot of the ANN output versus target values for nanofluid viscosity across the training, validation, and test datasets.

displayed in Figs. 8-9, respectively. Great agreement between the actual measurements and the ANN outputs, accompanied by negligible relative errors, demonstrates the robust predictive capability of the models for both viscosity and TC of the nanofluid investigated in this study.

The maximum relative errors observed on the test dataset are 0.8359% and 0.4069% for the viscosity- and TC-predicting ANNs, respectively, while the corresponding MSEs are 0.3425 % and 0.2465 %. These small values underscore the high accuracy of the trained networks in estimating nanofluid viscosity and TC for arbitrary nanoparticle weight fractions and temperatures.

For viscosity, the minimum, maximum, and mean

absolute errors (between the output of the trained ANN and the actual values of the entire experimental data) are 4.9204×10^{-4} cP, 0.0188 cP, and 0.0069 cP, respectively; the corresponding values for TC are 9.1383×10^{-5} W/m.K, 0.0054 W/m.K, and 0.0017 W/m.K. These negligible error margins corroborate the high accuracy of the developed ANN models in forecasting these two properties of the nanofluid under investigation.

Figs. 10-11 illustrate the response surfaces predicted by the trained neural network models for nanofluid viscosity and TC, respectively, and compare them with the experimental data as functions of nanofluid temperature and nanoparticle weight fraction in the base fluid.

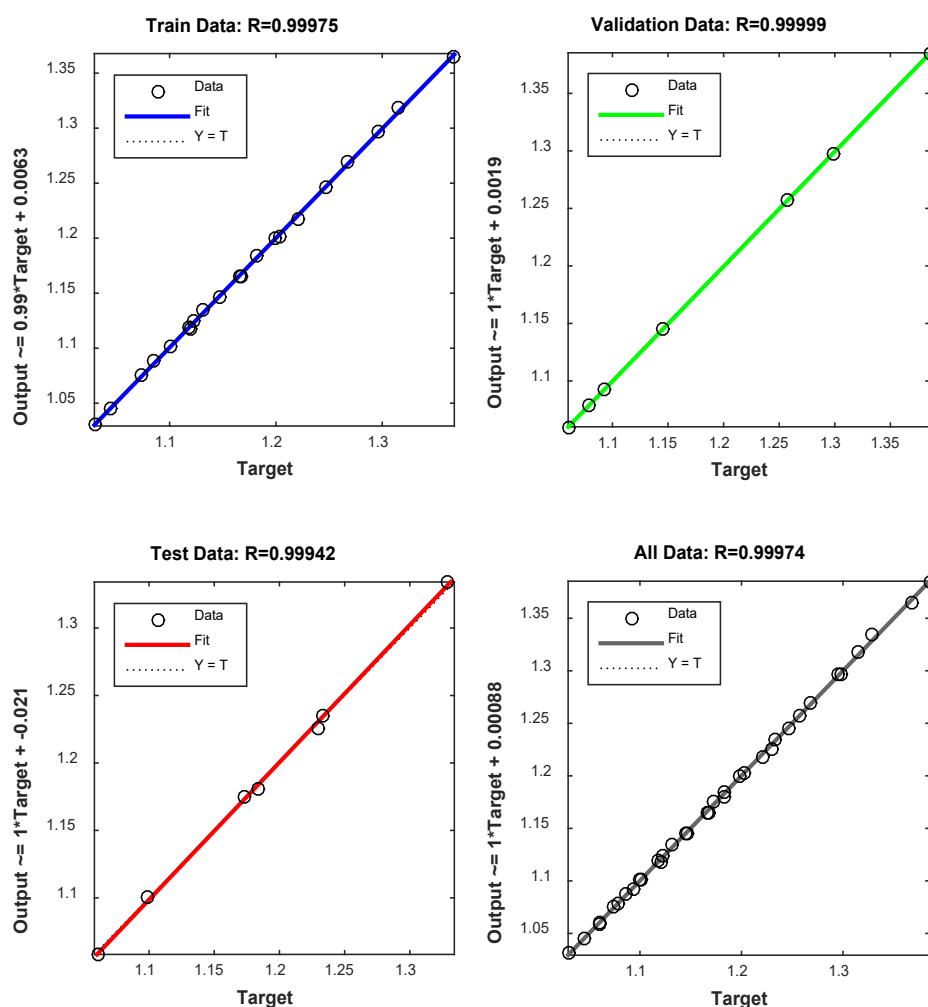


Fig. 5: Regression plot of the ANN output versus target values for nanofluid TC across the training, validation, and test datasets.

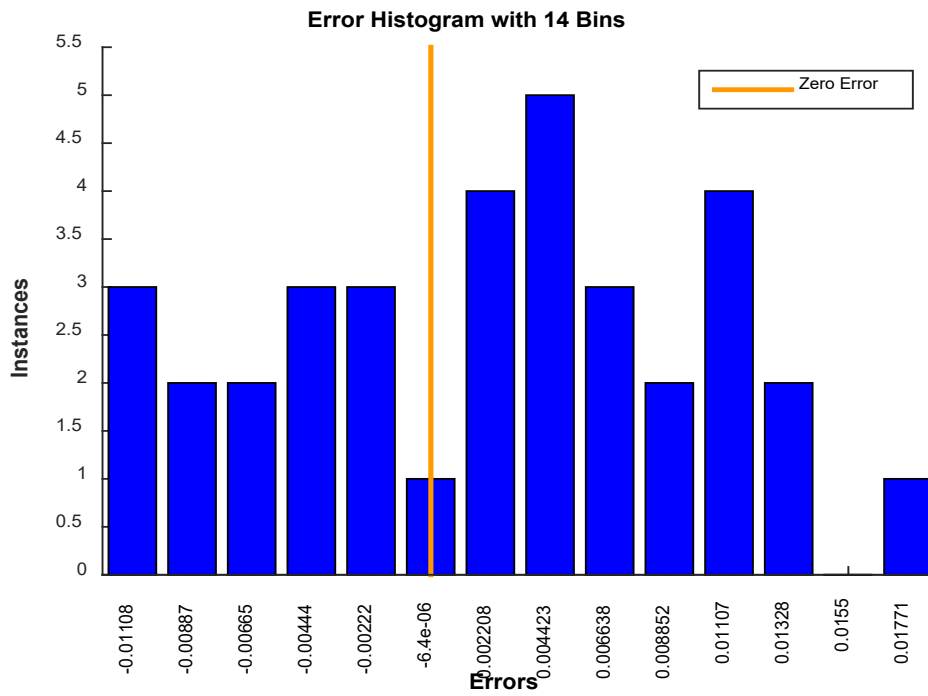


Fig. 6: Error histogram of the ANN output for nanofluid viscosity

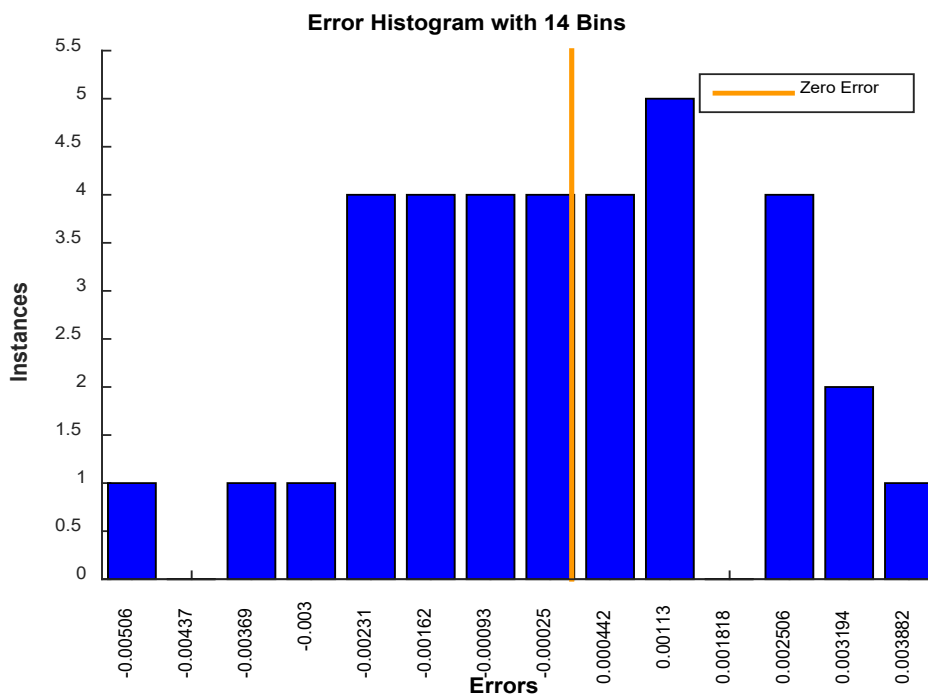


Fig. 7: Error histogram of the ANN output for nanofluid TC

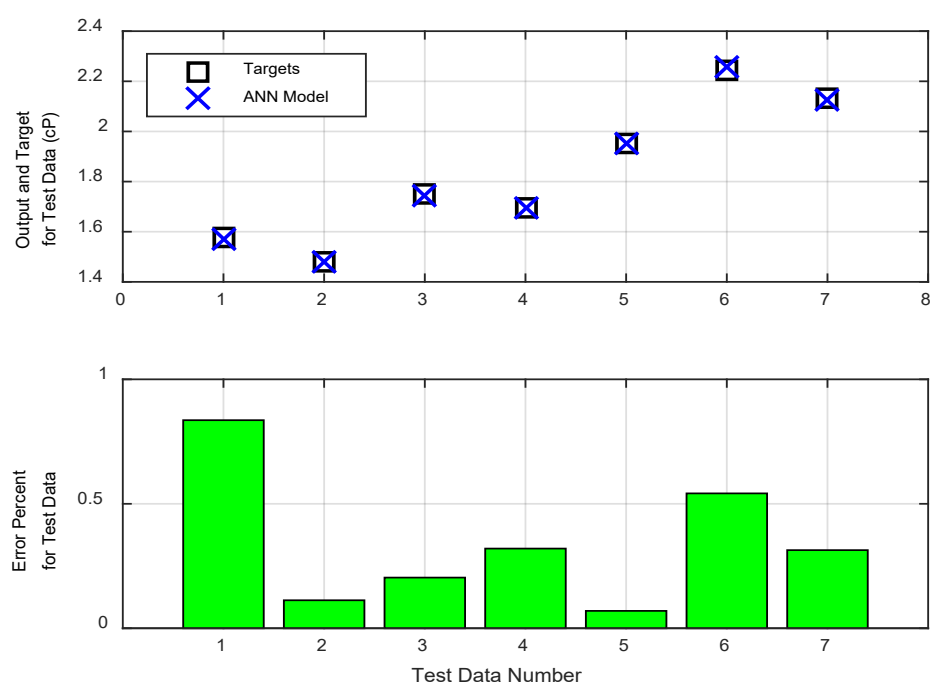


Fig. 8: Fitting profile and relative percentage error plot between the actual viscosity values and the corresponding ANN outputs for the test dataset

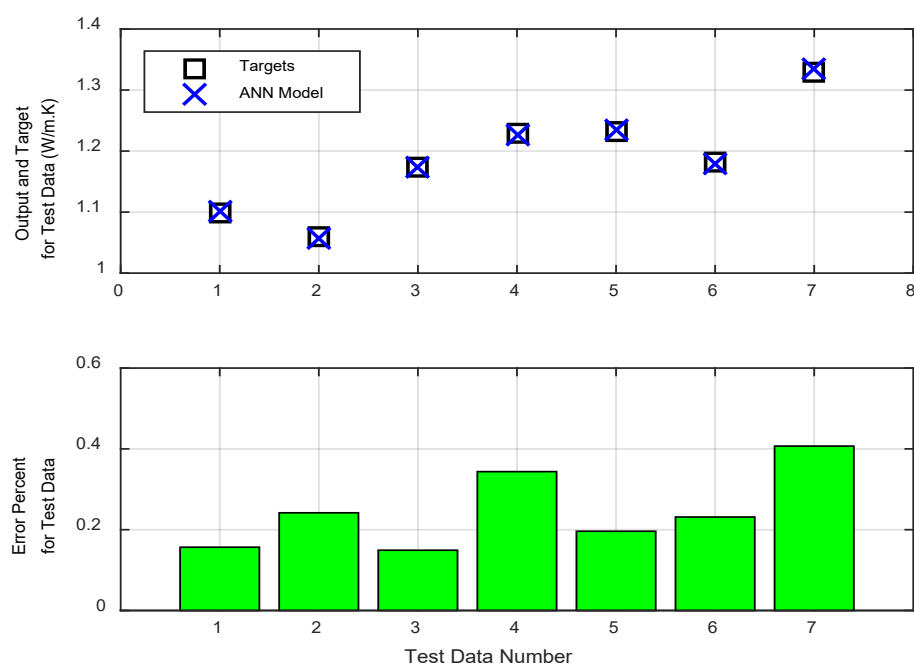


Fig. 9: Fitting profile and relative percentage error plot between the actual TC values and the corresponding ANN outputs for the test dataset

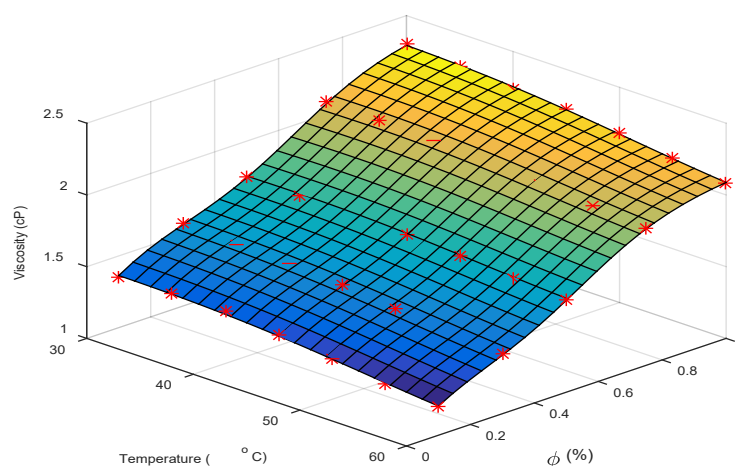


Fig. 10: Predicted viscosity surface generated by the trained neural network model as a function of nanofluid temperature and nanoparticle weight fraction, compared with the experimental data.

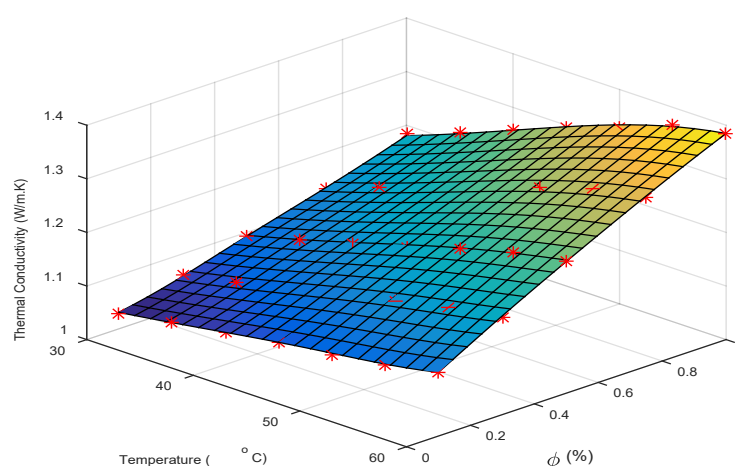


Fig. 11: Predicted TC surface generated by the trained neural network model as a function of nanofluid temperature and nanoparticle weight fraction, compared with the experimental data.

3- K-fold Cross-Validation

To comprehensively assess the forecasting capability and generalization of the developed ANN models, a K-fold cross-validation approach was implemented. This technique is a rigorous data resampling procedure, recognized as an optimal method for leveraging available data to obtain an unbiased assessment of a model's predictive power on previously unseen data. The process begins by randomly dividing the entire dataset into k equally sized segments, or folds. This division ensures every data point contributes to both the model's training and its subsequent evaluation, decreasing the

possibility of the total dependence of the assessment on a specific part of the data. During each round of the validation procedure, one unique fold is set aside as an independent validation set, while the remaining $k-1$ folds are combined to form the training dataset for the ANN. This cycle is systematically repeated k times, guaranteeing that every fold serves exactly once as the independent test group. The final model performance is derived by calculating the mean of the accuracy metrics across all k iterations. This averaging yields a more stable and reliable estimation of predictive accuracy compared to results from a single, arbitrary division of data into training and testing

sets. Furthermore, this methodology facilitates the detection of performance fluctuations across different data subsets. Analyzing this variance can reveal critical insights into the model's tendency to either overfit—memorizing training data—or underfit—failing to capture the underlying data patterns.

To assess the stable and highly reliable performance

of the designed networks, the coefficient of variation of errors (CV), defined as the ratio of the standard deviation of the output errors for test data to the mean of their corresponding target values, was calculated for each fold during the iterations of K-fold cross-validation with $k = 10$. The results are presented in bar charts in Figs. 12-13 for the viscosity-

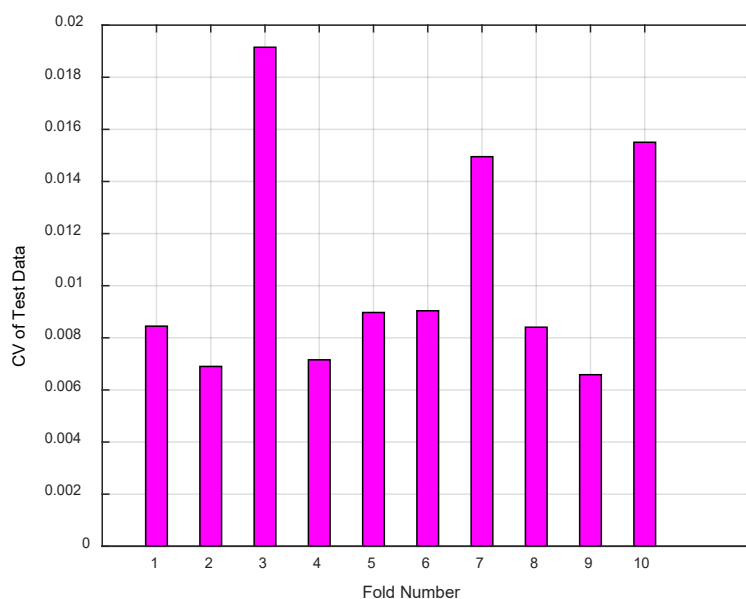


Fig. 12 CV of viscosity test data corresponding to 10 partitions generated by the K-fold Cross Validation

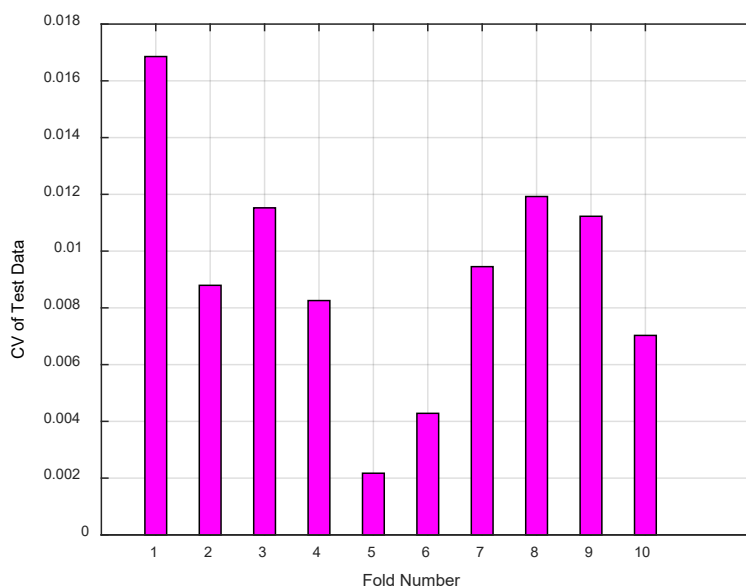


Fig. 13 CV of TC test data corresponding to 10 partitions generated by the K-fold Cross Validation

related network and the TC-related network of the nanofluid, respectively. The range of CV values for viscosity estimation was obtained between 0.0066 and 0.0192, while for TC estimation it ranged from 0.0022 to 0.0169 — all values remaining below 0.05. The mean CV for viscosity estimation was 0.0368, and for TC estimation it was 0.0258, indicating stable network performance and the absence of overfitting during the training process.

4- Sensitivity Analysis

To evaluate the influence degree of the weight fraction of nanoparticles and nanofluid temperature on the TC and nanofluid viscosity, and to determine the robustness of the outputs to small changes in the inputs, a sensitivity analysis has to be applied to the trained ANNs. To achieve this, the percentage change in the output of ANNs is computed by imposing 2- to 10-percent changes on each of the inputs only for test data. Tables 1-2 present the sensitivity analysis results and the values obtained for the average and maximum change percentage in the predicted nanofluid viscosity and TC.

According to Tables 1-2, as the changes in network inputs increase, the average and maximum changes also increase. These changes in network output are more obvious with changes in the nanofluid weight fraction. Thus, the influence of the input

value of weight fraction is greater on the outputs of ANNs compared with the effect of the input value of temperature. Moreover, the average and maximum changes of TC are much higher than the corresponding values of nanofluid viscosity for each change percentage in each ANN input. This means that the viscosity-predicting ANN model is more resistant to changes in the inputs and shows lower sensitivity compared with the TC-predicting ANN model.

5- Genetic Algorithm Optimization

In this study, the optimal nanofluid temperature and nanoparticle weight fraction were determined to simultaneously minimize viscosity and maximize TC. This multi-objective task was solved by a genetic algorithm (GA) code implemented in MATLAB R2015a. A weighted-sum approach was adopted, in which the objective function (Eq. 2) consists of a linear combination of the normalized nanofluid viscosity and the reciprocal of the normalized TC; adjustable weighting coefficients balance the relative importance of the two properties.

$$\text{Objective function} = \alpha \times \mu_{nf} + \beta / TC \quad (2)$$

The weights α and β , each bounded between 0 and 1 and constrained by $\alpha + \beta = 1$, quantify the

Table 1: The maximum change percentage in predicted TC and viscosity of nanofluid (μ_{nf}) owing to imposing 2- to 10-percent changes on ANN inputs for the test data

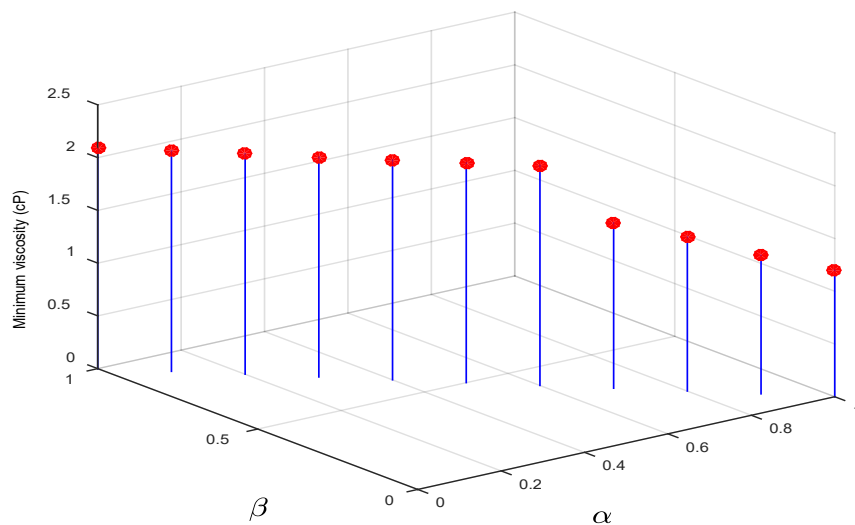
ANN Output	Change percentage in weight fraction					Change percentage in temperature				
	2	4	6	8	10	2	4	6	8	10
TC (W/m.K)	0.3425	0.6831	1.0217	1.3583	1.6928	0.2032	0.4030	0.5992	0.7917	0.9803
μ_{nf} (cP)	0.6169	1.2406	1.8705	2.5059	3.1461	0.2081	0.4157	0.6253	0.8355	1.0462

Table 2: The average change percentage in predicted TC and viscosity of nanofluid (μ_{nf}) owing to imposing 2- to 10-percent changes on ANN inputs for the test data

ANN Output	Change percentage in weight fraction					Change percentage in temperature				
	2	4	6	8	10	2	4	6	8	10
TC (W/m.K)	0.1894	0.3790	0.5688	0.7588	0.9490	0.1181	0.2359	0.3536	0.4712	0.5888
μ_{nf} (cP)	0.3851	0.7608	1.1275	1.4858	1.8363	0.1092	0.2175	0.3246	0.4304	0.5348

Table 3: Optimal conditions and predicted nanofluid properties for each α - β weighting combination in the multi-objective optimization.

α	β	Optimum Weight Fraction (%)	Optimum Temperature (°C)	Minimum nanofluid viscosity (cP)	Maximum TC (W/m.K)
0	1	1.0000	60.0000	2.0870	1.3847
0.1	0.9	1.0000	60.0000	2.0870	1.3847
0.2	0.8	1.0000	60.0000	2.0870	1.3847
0.3	0.7	1.0000	60.0000	2.0870	1.3847
0.4	0.6	1.0000	60.0000	2.0870	1.3847
0.5	0.5	1.0000	60.0000	2.0870	1.3847
0.6	0.4	1.0000	60.0000	2.0870	1.3847
0.7	0.3	0.4454	60.0000	1.5678	1.2293
0.8	0.2	0.3508	60.0000	1.4582	1.2003
0.9	0.1	0.1979	60.0000	1.3125	1.1512
1	0	0.1000	60.0000	1.2033	1.1189

Fig. 14: Minimum nanofluid viscosity versus viscosity weight coefficient (α) and TC weight coefficient (β) in the multi-objective optimization function.

relative priority assigned to viscosity reduction versus TC enhancement for the intended application. Regardless of the specific α - β combination, any decrease in the ANN-predicted viscosity or increase in the ANN-predicted TC lowers the value of the objective function, thereby driving the search toward the optimal point. The GA code is initialized with

a population of twenty chromosomes. In every generation, eighty percent of the individuals are recombined through uniform crossover, while thirty percent of the population is subjected to mutation with a 2 % mutation rate to preserve diversity and escape local optima. Iteratively refining the nanofluid temperature and nanoparticle weight fraction, the

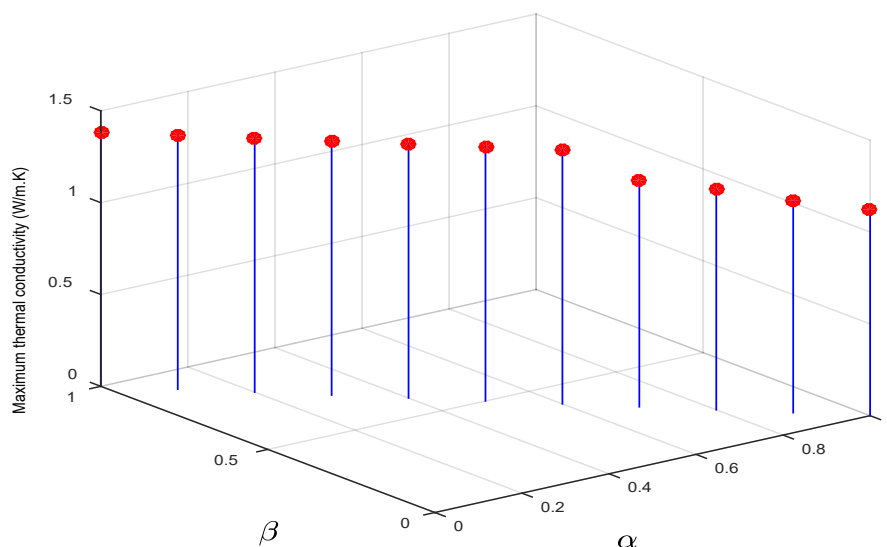


Fig. 15: Maximum TC versus viscosity weight coefficient (α) and TC weight coefficient (β) in the multi-objective optimization function.

algorithm converges toward the combination that achieves the best balance for the objective function, based on the weight coefficients.

Employing roulette-wheel selection, the algorithm preferentially propagates individuals that best balance viscosity and TC objectives, iterating until the 100-generation limit is reached. The routine was executed for $\alpha = 0, 0.1, 0.2, \dots, 1$ ($\beta = 1 - \alpha$), yielding—for each weighting pair—the optimal temperature and nanoparticle weight fraction together with the corresponding minimum viscosity and maximum TC reported in Table 3.

Fig. 14 depicts the minimum nanofluid viscosities obtained during optimization affected by the weight coefficients for nanofluid viscosity (α) and TC (β) in the objective function. Consistent with Table 1, raising α (thereby assigning greater priority to viscosity reduction) drives the optimized viscosity downward, confirming that the algorithm successfully reduces nanofluid viscosity whenever it is prioritized in the objective function.

Fig. 15 illustrates the maximum TC values obtained through optimization as functions of the weighting coefficients. In agreement with Table 3, elevating β (i.e., assigning greater priority to TC) does not monotonically raise the optimized TC, and thus, the algorithm may not achieve the optimal maximum TC, underscoring the limited sensitivity of the predicted maximum TC to its weighting in the objective function.

6- Conclusion

This study developed highly efficient ANN models for the simultaneous prediction of TC and viscosity of water-based nanofluids made of 50:50 graphene-oxide/silica (GO-SiO₂) nanoparticles over practical ranges of temperature and nanoparticle weight fraction. Our research results can be summarized as follows:

1) The TC ANN attains great accuracy, yielding R of 0.99975, 0.99999, 0.99942, and 0.99974 for the training, validation, test, and overall datasets, respectively, evidencing near-perfect agreement with experimental data. The viscosity ANN exhibits equally great performance, with corresponding R of 0.99978, 0.99981, 0.99977, and 0.99973, confirming its reliability across all data subsets.

2) Error-histogram analysis shows a pronounced peak at the zero-error bin for both ANNs, confirming that the vast majority of TC and viscosity predictions deviate negligibly from experimentally measured values and thereby corroborating the robustness of the training procedure.

3) Sensitivity analysis of the trained networks reveals that nanoparticle weight fraction exerts a stronger influence than temperature on both predicted TC and viscosity. Furthermore, the viscosity ANN exhibits lower sensitivity to input perturbations, indicating greater robustness compared with the TC ANN.

4) The optimal nanoparticle weight fraction ranges from 0.1% (when $\alpha = 1$) to 1% (when $\alpha \leq 0.6$), whereas the optimum temperature is consistently 60 °C across

every weighting scenario.

5) As the weighting shifts from TC ($\beta = 1-0.4$) to viscosity ($\alpha = 0-0.6$), the optimized nanofluid viscosity drops steeply from 2.0870 cP to approximately 1.2033 cP ($\alpha = 1, \beta = 0$).

6) Maximum TC rises appreciably from 1.1189 W/m.K ($\alpha = 1, \beta = 0$) to approximately 1.3847 W/m.K ($\alpha = 0-0.6, \beta = 1-0.4$) as emphasis on TC (β) intensifies.

Conflict of Interest

The authors affirm that they have no competing monetary interests that could influence the work reported in this paper.

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