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Prediction Of Properties And Stabilities Of Nanofluids Using Artificial Neural Network

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Abstract: Nanofluids offer significant potential for heat transfer because of their improved thermal properties. However, accurately predicting their thermal conductivity remains a challenge. This study tackles the issue by training a neural network using experimental data from various hybrid nanofluids. The study utilizes seven input factors, including volume concentration, temperature, and nanoparticle properties, to create ANN and SVR models using 200 data points. Model performance is evaluated using MSE and R^2, with ANN achieving an impressive R^2 of 0.99997 and SVR reaching 0.99788. These results confirm the models' high accuracy in predicting thermal conductivity across different nanofluid compositions. Additionally, a universal MLP-ANN formula is proposed for precise predictions.

Index Terms - Nanoparticle; Nanofluids; Artificial neural network (ANN); Stability Analysis; Regression Modelling; Thermal conductivity

I. Introduction

Nanofluids promise to revolutionize engineering and materials science by optimising the efficiency of systems. The suspension of nanoparticles in a fluid imparts novel characteristics, but their prediction of thermodynamic behaviour is yet to be simplified, which makes their applications restrained. Since the late 19th century, scientists have tried to formulate expressions for approximating the ability of a fluid containing spherical particles to transfer heat. the Maxwell proposed that the thermal conductivity of a fluid containing solid particles is influenced by the conductivity of both the base fluid and the particles, as well as their volume fraction. While Maxwell's model provides fairly accurate predictions for conventional nanofluids like Al_2O_3-based nanofluids, it significantly deviates when applied to hybrid nanofluids [1] [2]. To improve predictive accuracy, models such as the Hamilton-Crosse, Wasp, and Yu-Choi models have built upon Maxwell's work. However, despite these modifications, these models still struggle to accurately examines how well traditional and hybrid nanofluids conduct heat.

The variances in existing models probably stem from their failure to account for all factors influencing nanofluid thermal conductivity. The most important variables are base fluid and nanoparticles' heat transfer, particle shape, Accumulation over time, volumetric concentration, surface layers, temperature, and mixture ratios in hybrid nanofluids [3]. Each factor interacts uniquely with thermal conductivity. For example, higher base fluid and nanoparticle conductivity increase overall thermal conductivity, while smaller nanoparticles enhance it but also accelerate aggregation. Although regression correlation equations have been developed for various nanofluids such as Al_2O_3-water, TiO_2-water, and CNT-Fe_3O_4-water—they remain limited to specific experimental ranges. To improve prediction accuracy, researchers have adopted AI and machine learning models. like MLP, RBF, LSSVM, ANFIS, GA-ANN, and hybrid neuro-fuzzy systems [4] [5]. These models offer broader and more precise thermal conductivity predictions, overcoming the limitations of traditional and regression-based approaches [7].

I. MODELLING METHODS

- **Support vector regression**

Support vector regression (SVR) and Support vector classification (SVC) are both extensions of Support vector machines (SVM). SVR, developed by Vapnik, is used for regression problems and has been widely used in engineering applications. It aims to model the nonlinear relationship between input and output variables while minimizing prediction error [8][9].

The SVR model works by a regression function y=f(x) that best fits the ε-SVR model. in order to precisely forecast target values {Yi} from respective input variables {Xi}. Having training data in the form of (Xi,Yi), Where x and y are input and output scalar vectors, the model represents the nonlinear relationship by transforming the input data into a higher dimensional space using a nonlinear mapping function {hi(x)}.

- **Artificial Neural Networks**

Traditional modelling struggles to capture complex or nonlinear relationships between input and output data. Artificial neural networks (ANNs) effectively map these relationships by mimicking the functionality of human brain. ANN applications span various fields, including pattern recognition, classification, and estimation. ANNs consist of interconnected artificial neurons, similar to biological neurons, with perceptron's forming input, hidden, and output layers. Multilayer perceptron (MLP) is the most popular ANN structure, aimed at mimicking human learning processes [10] [11]. The study employs various learning algorithms like Levenberg-Marquardt (LM), scaled conjugate gradient (SCG), Bayesian regularization (BR), and resilient propagation (RP) to enhance the model's performance. Signals pass through layers using nonlinear transfer functions, with weighted inputs transformed by activation functions at hidden neurons before reaching the output layer. Finding an optimal MLP model can be challenging, but using different algorithm variations improves efficiency [12][13].

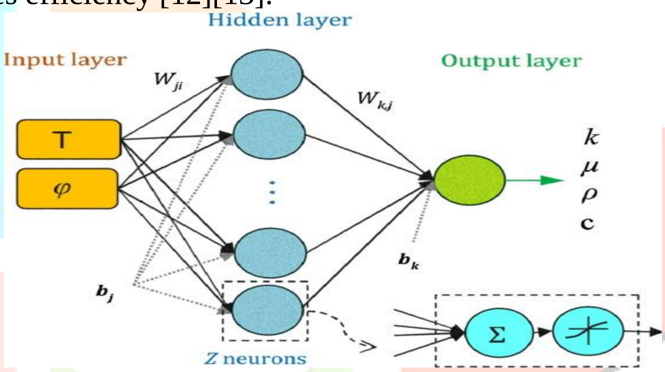

Fig.1 MLP neural network schematic diagram.

II. COMPUTATIONAL METHODOLOGY

The calculations in this research were carried out using MATLAB 2018a. When modeling the relative thermal conductivity of hybrid nanofluids, several key variables are considered, including volume fraction, mixture ratio, base fluid acentric factor, temperature and the thermal conductivity, density, and size of the nanoparticles.

In order to improve training effectiveness and avoid convergence to a local optimum, the dataset has to be preprocessed. The data is scaled to a range between 0 and 1 before training and testing, and then restored to its original scale after the model is trained.

- **Dataset**

An extensive review of existing research on the thermal conductivity of hybrid nanofluids was conducted, 200 experiment data points were gathered from 50 different sources. These investigations enabled the identification of the most important parameters that affect hybrid nanofluids' thermal conductivity to a great extent. Factors affecting the thermal conductivity of hybrid nanofluids include temperature, particle size, surfactant use, volume concentration, nanoparticle shape and size, zeta potential and the thermal conductivity of the nanoparticles. Additionally, the type of base fluid and the ratio of nanoparticle mixing significantly influence the thermal conductivity. To develop a comprehensive and accurate predictive model that can generalize across various hybrid nanofluids, it was essential to select the most influential parameters. In this research, the input features chosen for the algorithm are volume concentration, particle size, pH, Viscosity, temperature and the acentric factor of the base fluid. The addition of the acentric factor enables discrimination between different base fluids and improves model accuracy. Acentric factor, being vital to predict the critical properties of mixed fluids, was computed via Kay's equation, as applied in the work by Khalif and Vaferi. The training and validating data set specifications applied in training and cross-validation of Artificial Neural Network (ANN).

III. RESULTS AND DISCUSSION

This part evaluates the performance of different prediction methods by comparing their outcomes to determine the most effective technique. Finally, the relative prediction error is ascertained for each method.

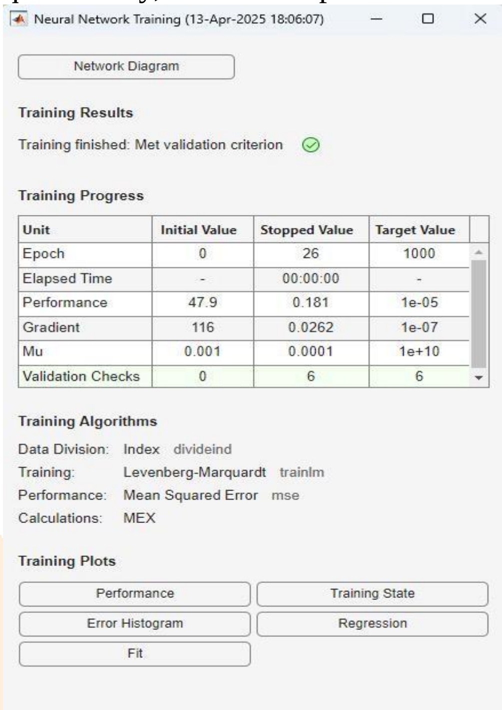

Fig.2 Training of Neural network.

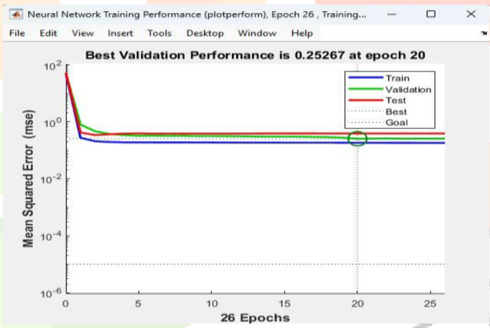

Fig.3 Performance

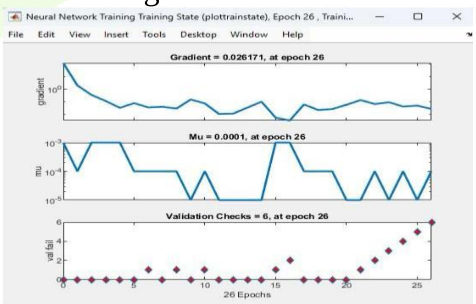

Fig.4 Training State

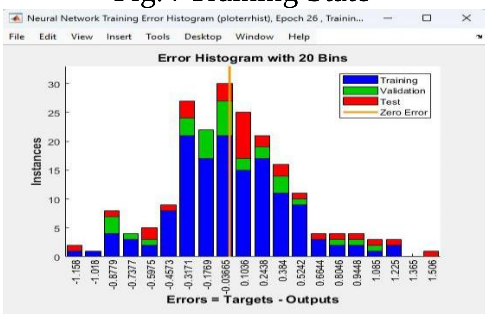

Fig.5 Error Histogram

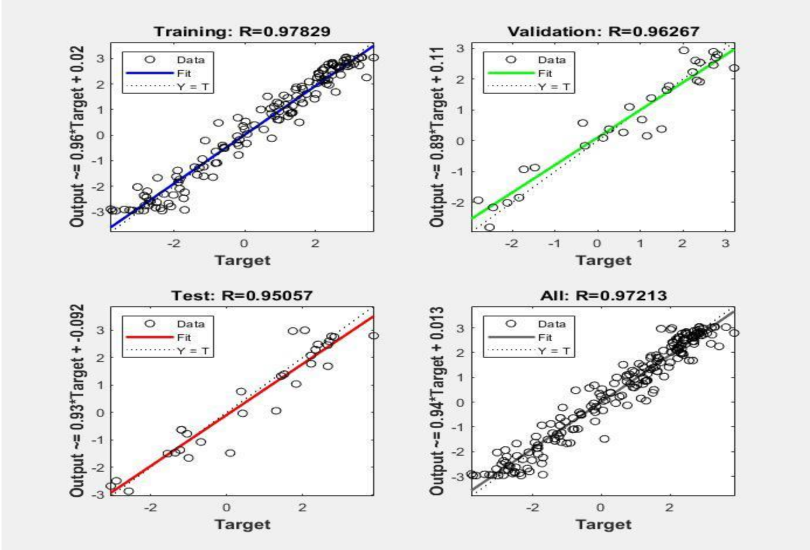

Fig.6 Regression

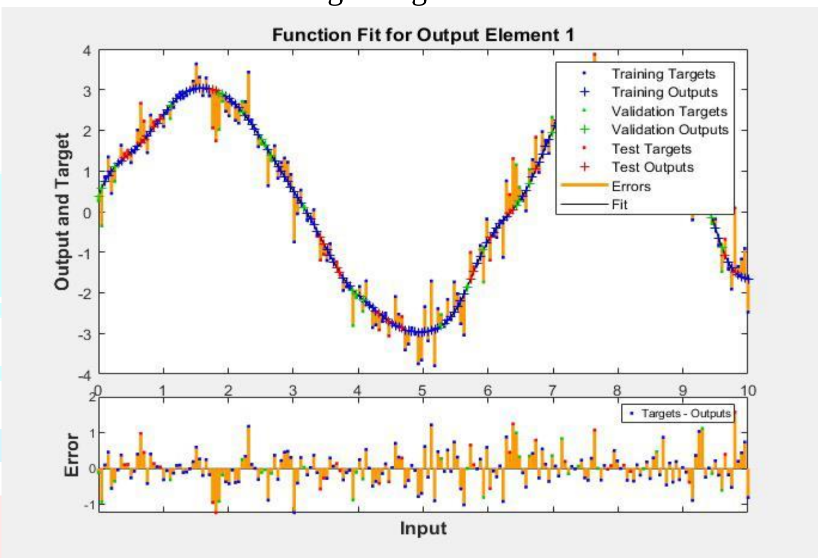

Fig.7 Fit

V Conclusion

This research aims to enhance the development of thermal applications in engineering systems by addressing the challenge of accurately predicting the thermal conductivity of hybrid nanofluids. Accurate prediction models are needed in order to optimize the execution of nanofluids in numerous heat systems where efficiency and heat transfer properties are vital.

In in this paper, a smart model to forecast the thermal conductivity of hybrid nanofluids of varying types has been created to approximate the same. The predictive model is drawn up on ANN topology and formulated in such a manner that the intricately interlinked, nonlinear parameters between varied inputs and thermal conductivity results can be captured through model.

The model utilizes seven key input variables: nanoparticle volume concentration, temperature, base fluid acentric factor, nanoparticle density, and the ratio of nanoparticles in the mixture, as well as the thermal conductivity and nanoparticle size. These were selected cautiously depending on their importance to heat transfer performance.

A dataset consisting of 200 experimental measurements was compiled from various published research articles. This dataset was utilized to train and validate the neural network model, ensuring it has sufficient generalization capability and predictive accuracy across a wide range of hybrid nanofluid compositions and operating conditions.

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