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RESEARCH ARTICLE

Sustainable Viscosity Prediction of Hybrid Alumina-Copper Oxide Nanofluid for Green Heat Transfer Applications Using Adaptive Neuro-Fuzzy Inference System (ANFIS)

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ABSTRACT

Developing more energy-efficient, environmentally friendly heat transfer solutions is necessary. As a result, the application of nanofluids has attracted an increasing amount of attention. This paper shows a new method for predicting the viscosity of hybrid alumina-copper oxide nanofluid. The Adaptive Neuro-Fuzzy Inference System (ANFIS) was used to predict the abovementioned physical property of the fluid dispersed in Therminol 55; a medium-temperature medium. The concentration of nanoparticles, temperature, and shear rate were found to be the major input factors. In comparison to Decision Trees (DT) and Support Vector Regression (SVR), the ANFIS method model was more effective, yielding a Root Mean Square Error (RMSE) of 1.0278. The Mean Squared Errors (MSE) for the DT and SVR models were 96.67% and 97.75% higher, respectively, compared to the ANFIS model. It was also discovered that the viscosity is higher at lower temperatures of 32.63 °C and a maximal nanoparticle concentration of 1%. It reached 34.34 mPa.s. It may also be emphasized that hybrid nanofluids, such as those incorporating alumina-copper oxide nanoparticles, exhibit lower viscosities at elevated temperatures compared to single-nanoparticle fluids, indicating their potential for optimizing heat transfer applications. It implies that they can be used to optimize the heat transfer application described in this paper. In conclusion, ANFIS is a powerful tool for predicting viscosity. The use of such instruments allows designers to create more effective, as well as environmentally friendly heat transfer systems. This study is, therefore, another example of “green engineering” solutions.

Keywords: Hybrid nanofluid, Viscosity, Adaptive neuro-fuzzy system

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1. Introduction

In pursuing more sustainable and environmentally responsible industrial practices, green engineering has emerged as a critical approach for developing systems that minimize environmental impact while maximizing efficiency. Central to this concept is the need for improved heat transfer fluids that can enhance energy efficiency and reduce waste [1]. Nanofluids, which are fluids enhanced with nanoparticles, have gained significant attention for their potential to improve heat transfer processes while contributing to the goals of green engineering [2]. The thermal properties of nanofluids, such as enhanced thermal conductivity and heat transfer efficiency, directly contribute to reducing energy consumption in various industrial applications. Their viscosity properties, when optimized, ensure efficient fluid flow, minimizing the energy required for pumping and circulation [3]. These improvements align with green engineering principles by promoting energy efficiency, reducing operational costs, and lowering carbon emissions. For instance, in solar thermal systems, nanofluids enable higher heat absorption and storage, reducing reliance on non-renewable energy sources [4]. Similarly, in cooling systems for industrial processes and electric vehicles, the improved thermophysical properties of nanofluids minimize energy wastage, supporting global sustainability goals.

By reducing overall energy consumption and improving heat dissipation, nanofluids offer a promising path toward more sustainable and energy-efficient thermal management systems [5]. Specific applications where these advances can provide significant environmental benefits include industrial cooling systems, where enhanced heat transfer efficiency reduces energy consumption and greenhouse gas emissions, solar thermal energy storage systems that maximize energy capture and reduce reliance on fossil fuels, and HVAC systems in green buildings, where nanofluids contribute to improved thermal regulation and lower operational energy costs [6–8]. Additionally, automotive thermal management systems, including electric vehicle battery cooling, benefit from nanofluids, reducing the risk of overheating while improving energy efficiency and extending battery life.

The viscosity of heat transfer fluids is a critical factor in the energy efficiency of thermal systems. It has been established that nanofluids, especially when they contain hybrid nanoparticles, may significantly affect the thermal properties of base fluids and, therefore, substantially increase the heat transfer capability of these fluids. In numerous technical and industrial applications, it is highly important to manage thermal energy efficiently, and systems must be designed to dissipate as much heat as possible to make them more reliable and efficient. The altered viscosity of heat transfer fluids in media that uses hybrid nanoparticles is especially important in this new technology [9, 10]. Hybrid alumina-copper (Al_2O_3-CuO) oxide nanoparticles offer promising prospects for enhancing heat transfer efficiency in medium-temperature applications. Hybrid nanofluids, such as Al_2O_3-CuO, combine the thermal conductivity of CuO with the stability and lower viscosity impact of Al_2O_3, making them more effective for medium-temperature applications [11]. This synergy provides improved heat transfer performance without significantly increasing pumping power requirements, ensuring their suitability for such conditions. These nanoparticles can alter base fluids' viscosity, thus influencing their thermal performance [12–14]. Understanding and predicting the viscosity of such nanoparticle dispersions are crucial to optimizing heat transfer processes.

Plant and Saghir [12] Studied the heat transfer enhancement of CuO-Al_2O_3 nanocomposite particles in porous metal foam by experimental and numerical methods. Interestingly, even small amounts of copper improved thermal performance. A recent study by Ahmad et al. [15], presented a novel investigation of the heat and mass transfer behaviors of copper-aluminum oxide hybrid nanoparticles in a porous medium. They found that the presence of a porous medium results in a substantial increase in shear stresses and heat transfer rates. Kapen et al. [16] offered a comprehensive investigation into the stability of (Cu-Al_2O_3)/water hybrid nanofluid flow in porous media under the influence of hydromagnetic, suction, and injection effects. Their discoveries illuminate the variables that influence the stability of flow and the occurrence of transition phenomena.

Shahabi Nejad et al. [17] investigated the impact of critical factors, including Reynolds number, nanofluid concentration, and porosity, on the heat transfer performance of Al_2O_3–Cu/water hybrid nanofluid in porous tubes, elucidating the positive influence of porous media on thermal efficiency. Azman et al. [18] evaluated the performance of Al_2O_3-CuO/water hybrid nanofluid in enhancing heat transfer efficiency through numerical investigation of flow characteristics in sawtooth corrugated pipes, offering insights for optimizing heat transfer systems design. The viscosity investigation of hybrid Al_2O_3-CuO oxide nanoparticles is paramount as highlighted by the reviewed articles [12, 15–18], demonstrating its crucial role in understanding and optimizing

heat transfer processes in various applications, from porous media flows to corrugated pipe systems.

Utilizing machine learning methods for viscosity prediction on hybrid nanoparticles offers a sophisticated approach to understanding complex relationships governing fluid behavior, enhancing accuracy and insights crucial for optimizing heat transfer processes [19, 20]. Parashar et al. [21] investigated the dynamic viscosity of MXene-palm oil nanofluid, revealing temperature-dependent behavior and developing a robust multilayer perceptron artificial neural network model for accurate viscosity prediction. Adun et al. [22] comprehensively investigated the thermal conductivity and dynamic viscosity behaviors of Al_2O_3-ZnO-Fe_3O_4 ternary nanofluid, exploring various mixture ratios and volume concentrations and developing a highly accurate machine learning model for prediction. Lashari et al. [23] employed response surface methodology and supervised machine learning techniques to model nanopolymeric viscosity, demonstrating the effectiveness of these approaches in characterizing and predicting viscosity behaviors of GO-SiO_2/HPAM composite. Olumegbon et al. [24] presented a support vector regression (SVR) model for predicting the viscosity of carbon-based nanomaterials dispersed in diesel oil, demonstrating high accuracy and outperforming existing models, thus facilitating the efficient design of heat transfer applications. Esfe et al. [25] employed Artificial Neural Network combined with Principal Component Analysis to accurately predict the dynamic viscosity of MWCNT-Al_2O_3 (30:70)/Oil 5W50 hybrid nano-lubricant, demonstrating good agreement with experimental data and outperforming other data processing methods.

Adun et al. [26] introduced a novel Optimizable Gaussian Process regression approach to accurately predict the viscosity of hybrid nanofluids for solar thermal applications, demonstrating superior predictive performance compared to other machine learning algorithms. Sepehrnia et al. [27] investigated the effects of Graphene Oxide, Silica Aerogel, and multi-walled carbon nanotubes in oil (5W30) on viscosity and wear properties, modeling them accurately using machine learning. Hua et al. [28] employed a multilayer perceptron artificial neural network model to accurately predict the dynamic viscosity of a hybrid antifreeze containing MWCNTs and alumina, revealing significant impacts of Solid Volume Fraction and temperature, crucial for heat exchanger design in portable devices. Borode and Olubambi [29] evaluates response surface methodology, multilayer perceptron, and adaptive neuro-fuzzy inference system (ANFIS) for predicting viscosity and relative viscosity of GNP-alumina hybrid nanofluid, with ANFIS demonstrating superior performance metrics, emphasizing its potential for accurate viscosity predictions.

While recent studies [21–29] have extensively investigated the thermal properties and heat transfer enhancements of hybrid nanofluids containing Al_2O_3-CuO oxide nanoparticles, a notable gap in the literature regarding accurate prediction methods for viscosity in such complex fluids remains. Prior research has predominantly concentrated on conducting experimental measurements and numerical simulations to comprehend the behavior of these nanofluids across different circumstances [30, 31]. Despite the significant advancements in understanding the thermal properties of hybrid nanofluids, there remains a notable gap in accurately predicting their viscosity, which is crucial for optimizing the efficiency of heat transfer systems in sustainable applications.

Previous research has predominantly focused on experimental measurements and numerical simulations to assess the behavior of hybrid nanofluids. However, the development of predictive models, particularly those utilizing advanced machine learning techniques such as ANFIS, has been limited. This study addresses this gap by proposing a novel approach to predict the viscosity of hybrid alumina-copper oxide nanofluids, combining the benefits of fuzzy logic and neural networks to capture the complex relationships between input parameters like nanoparticle concentration, temperature, and shear rate. By providing a more accurate and reliable model for viscosity prediction, this work contributes to the optimization of green engineering solutions, advancing the use of nanofluids in energy-efficient heat transfer systems and supporting the global shift toward sustainable technologies. Incorrect viscosity predictions can lead to significant challenges in real-world applications. For instance, underestimating viscosity may result in insufficient pumping power, leading to poor heat transfer performance and overheating in critical systems such as electric vehicle batteries or industrial cooling setups. Conversely, overestimating viscosity can cause excessive energy consumption for fluid circulation, reducing overall system efficiency and increasing operational costs. Accurate predictions are crucial for designing optimized systems that balance heat transfer efficiency with minimal energy usage, thereby aligning with sustainability objectives.

2. Materials and methods

This section consists of two parts, including the employed method for preparing nanofluids and the machine learning approach in this research.

2.1. Preparation of nanofluid

The first stage of the process involves the careful preparation of materials. High-purity alumina oxide and copper oxide nanoparticles, sourced from Us Research Nanomaterials, Inc. (Houston, TX, USA), are selected for their quality and consistency. With an average size of 20–50 nm, these nanoparticles closely match the useful range for both stable dispersion and effective enhancement of heat conductivity. The base fluid is obtained from Merck, India (Therminol, 55) and the fluid is stored free of impurities in conditions that maintain its essential properties.

Therminol 55 is preheated to about 50°C to lower its viscosity and ensure effective mixing and dispersion. This viscosity reduction is a crucial first step, as it helps the nanoparticles spread more evenly throughout the fluid. This is then followed by adding the respective amounts of nanometer-sized alumina and copper oxide to be synthesized, starting at a concentration of 0.1 weight % by using the stirring procedure. The nanoparticles were dispersed into the pre-heated Therminol 55, and stirring was continued throughout. The mixture is then sonicated with an ultrasonic probe to add more homogeneity to the dispersion.

The procedure is followed for higher weight percentages of nanoparticles i.e. 0.3%, 0.5%, 0.8%, and then for the highest weight percentage of 1%. Next, the synthesis of copper/alumina hybrid nanoparticles with 10:90, 20:80, and 30:70 weight ratios of copper oxide to alumina oxide have been formulated. There are 5 concentrations at which the blend is formulated (0.1, 0.3, 0.5, 0.7, and 1.0% by each ratio) allowing a complete examination of various nanoparticle forms within that carrier liquid as well as understanding its properties consistently across ranges in composition.

2.2. Machine learning

ANFIS is a candidate for the most accurate machine learning model in predicting hybrid Al_2O_3-CuO oxide nanoparticles based on research conducted by [29]. However, the dataset underwent several preprocessing steps before constructing the ANFIS model for predicting the viscosity of hybrid Al_2O_3-CuO oxide Nanoparticles. Firstly, any out-of-range data resulting from system malfunctions or sensor faults were removed to ensure the integrity of the dataset. The data was then standardized and normalized to reduce complexity and enhance model efficiency. Standardization was achieved by applying the following:

$$\sigma_{x_i} = \frac{x_i - \tilde{x}}{\sigma_x} \quad (1)$$

where x_i represents raw input data, σ_{x_i} denotes standardized input data, σ_x represents the standard deviation and $\tilde{x}$ signifies the average deviation of the data [32].

Besides, the dataset was divided into two parts: 144 training samples and 36 test samples. This division guarantees that the model's performance is thoroughly assessed on data that it has not previously encountered. The ANFIS model was utilized to forecast the viscosity of hybrid Al_2O_3-CuO oxide Nanoparticles, taking into account different cutting process parameters, including feed speed, rotation speed, and depth of cut. The proposed ANFIS model demonstrated superior predictive performance with an RMSE of 1.0278, significantly outperforming Decision Trees (DT) and Support Vector Regression (SVR), whose RMSE values were 96.67% and 97.75% higher, respectively. Additionally, the ANFIS model achieved an R-value of 0.9911, indicating a near-perfect correlation between predicted and experimental data, making it highly reliable for viscosity prediction in complex nanofluid systems. The ANFIS system, which combines fuzzy logic and artificial neural networks, was selected for its capacity to address nonlinear and intricate problems efficiently. ANFIS's adaptive machine learning capability allows it to model complex, nonlinear relationships between input parameters such as temperature, nanoparticle concentration, and shear rate. By integrating the strengths of fuzzy logic and neural networks, ANFIS captures the inherent uncertainties and complexities of nanofluid behavior while iteratively refining its predictions through backpropagation. This makes it ideal for predicting viscosity, a property influenced by multiple, highly nonlinear factors, ensuring both accuracy and robustness in real-world applications. The ANFIS operations were governed by precise rules, which mapped inputs such as cutting parameters to outputs such as tool force and workpiece surface roughness.

The ANFIS structure consists of five layers, each with a distinct role in processing input data and producing output predictions. Membership functions are utilized in the initial fuzzification layer to convert input data into linguistic variables, which represent the extent of truth for each fuzzy set. These linguistic variables are then passed on to subsequent layers for additional processing. The second layer, known as the rule layer, determines the firing strength of each fuzzy rule by aggregating the linguistic variables associated with input features. This layer accurately quantifies the impact of each rule on the overall prediction. When it comes to the third layer – the normalization layer, is responsible for modifying the firing strengths of various rules. Such changes are vital to ensure the overall consistency and coherency of all rules. The

values that are normalized are produced by dividing the firing strength of definite rules by the contribution of all rules. Such results may indicate the relative impact of every rule in terms of generation predictions. After the process of normalization is over, it is possible to unite the normalized firing strength and consequent parameters: a set of coefficients of a linear function used to generate rules' outputs. It is reached with the help of the next layer called the defuzzification layer. Finally, it is possible to predict an exact value for a specific input in the fifth layer, also known as the output layer. Initial results from all rules have to be the response. The latter can be achieved with the help of aggregation, such as weighted summation or integration of several rule results. Such a prediction represents a general system response determined with the help of input data and a set of fuzzy rules.

The structure of ANFIS allows for both forward and backward information passes, enabling iterative adjustments to the model parameters through a process akin to gradient descent optimization. By iteratively minimizing prediction errors using training data, ANFIS optimizes its fuzzy rule base and consequent parameters to improve predictive accuracy. This adaptive learning capability makes ANFIS well-suited for modeling complex and nonlinear relationships in various domains, including engineering, finance, and control systems.

After establishing the ANFIS architecture, the model's hyperparameters were selected using trial and error to reach the highest accuracy. The root mean square error (RMSE) was utilized as the objective function to extract the optimal hyperparameters. Fig. 1 shows the extracted hyperparameters of the proposed ANFIS to reach the highest accuracy in predicting viscosity. This iterative process aimed to minimize training errors and improve the model's predictive accuracy. The overall methodology ensures the robustness and reliability of the ANFIS model for predicting the viscosity of hybrid Al_2O_3-CuO oxide Nanoparticles, contributing valuable insights to thermal management and nanofluid applications. The pseudocode for ANFIS model development is shown below:

3. Results and discussion

3.1. Viscosity

Fig. 2a shows the relationship between Therminol 55's viscosity and temperature and three different kinds of nanofluid with different proportions: CuO-Al_2O_3 Therminol 55 at a fixed temperature. It can generally be observed from all instances that the viscosity of a fluid decreases with an increase in temperature. This can be regarded as typical behavior for heat transfer fluids. In Fig. 2a, the addition of CuO nanoparticles (at 0.1%, 0.3%, 0. 5%, and 1.0% concentrations) increases the viscosity relative to pure Therminol 55 and primarily at lower temperatures. However, this difference gradually diminishes as the temperature rises further, trending toward a viscosity quite similar for all concentrations around 80 °C in some cases. Thus, we infer that CuO increases fluid viscosity, especially for low temperatures. Yet it has less effect as the fluid temperature increases. Fig. 2b shows that with the addition of Al_2O_3 nanoparticles, a similar trend occurs in Fig. 2a. As the proportion of Al_2O_3 increases, the viscosity of Therminol 55 increases. When the concentration is higher, the same trend is more pronounced. Compared to the addition of CuO at equal concentrations, Al_2O_3 appears to have slightly less effect on viscosity. This is the same as CuO also: as the temperature increases, the differences in viscosities among concentrations diminish [33]. Figure a In this case, the viscosity of the base fluid shows that Al_2O_3 too is a function of temperature, but as temperatures increase, its effect diminishes and disappears altogether at least that which remains after cooling to room temperature again Evidently, the base fluid's viscosity is also a function of temperature, but is only very temperature sensitive for fluid in the top thermal boundary layer near walls. Fig. 2c and Fig. 2d describe hybrid CuO-Al_2O_3 nanofluids. The viscosity of these hybrid nanofluids follows the same pattern as individual nanoparticles: A similar trend is visible in Fig. 2e viscosity decreases as temperature increases. The hybrid nanofluids as a rule at equivalent concentrations will have lower viscosities than those containing CuO or Al_2O_3 only, possibly owing to a synergistic effect.

The hybrid formulas at different concentrations may optimize thermal mechanical properties, and level out viscosity changes [34]. For the higher host fluid concentrations of the nanofluid hybrids, viscosities are still higher at lower temperatures. But as the temperature goes up, these differences are narrowly reduced. This suggests that the hybrid nanoparticles can enhance heat transfer by reducing viscosity at higher working temperatures, in contrast to its fall at lower temperatures. As a result of the above, we now believe that while adding nanoparticles raises the viscosity of Therminol 55, encapsulated variants are beneficial in that at high temperatures they offer some relief for excessive viscosity increases and are probably more suitable as media to bearer for medium-grade heating applications. When comparing the viscosity patterns of Therminol 55 infused with nanoparticles to the base fluid alone, it is clear that the inclusion of nanoparticles leads to an

```
Algorithm: ANFIS for Predicting Thermal Conductivity and Viscosity
Input: Training data (temperature, concentration, nanoparticle ratio),
      Target data (thermal conductivity, viscosity)
Output: Predicted thermal conductivity and viscosity
Step 1: Data Preprocessing
   - Normalize input and output data to range [0, 1].
   - Split dataset into training (80%) and testing (20%) sets.
Step 2: Initialize ANFIS Structure
   - Define input parameters: Temperature (T), Concentration (C), Nanoparticle Ratio (R).
   - Set number of membership functions for each input (e.g., 3 Gaussian functions per input).
   - Initialize fuzzy rules based on input-output relationships.
Step 3: Training ANFIS Model
   For each epoch in training iterations:
      1. Compute output for each rule using:
        - If-Then rules: "IF (T is A) AND (C is B) AND (R is C) THEN (Output = D)"
      2. Calculate error between predicted and actual values (MSE).
      3. Backpropagate error to update parameters (membership functions, rule weights).
Step 4: Validate Model
   - Use testing data to predict thermal conductivity and viscosity.
   - Calculate Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for validation.
Step 5: Model Optimization
   - Adjust number of rules or membership functions for improved accuracy (if needed).
  - Repeat training if performance is not satisfactory.
Step 6: Model Deployment
   - Use final ANFIS model to predict thermal conductivity and viscosity for new inputs.
   - Visualize predicted vs. experimental results for comparison.
End.
```

Fig. 1. The pseudocode for ANFIS model development.

increase in viscosity at all recorded temperatures [35]. The increase in resistance to flow is a result of the improved interaction between the nanoparticles and the molecules of the fluid [36]. This phenomenon occurs at every concentration from 0.1% to 1.0%. However, as the concentration of nanoparticles rises, the increase in viscosity becomes more noticeable. The decrease in viscosity with rising temperature, including for fluids containing nanoparticles, is an essential thermophysical characteristic of liquids [37].

Nanoparticles have an impact on the temperature-viscosity connection, but they do not change the underlying inverse relationship between these two parameters [38]. Research conducted by Awais et al. [39] examined nanoparticle form's impact on nanofluids' thermal conductivity. This work provides valuable insights into thermal behavior and rheological parameters, such as viscosity. In a study conducted by Murshed et al. [40], a thorough examination was conducted to investigate the improved thermal conductivity of TiO_2 and Al_2O_3 nanofluids. The study also provided valuable insights into the changes in viscosity that may be compared to other findings. Overall, the presented graphs unambiguously demonstrate the influence of adding nanoparticles and adjusting their concentration on the viscosity of Therminol 55. It is evident that the viscosity increases as the number of nanoparticles rises. The variations in viscosity have a notable impact on applications that need accurate regulation of fluid dynamics and thermal characteristics, such as heat transfer systems [41]. The decrease in viscosity with temperature is constant for all mixes, following the accepted thermophysical behavior of fluids.

3.2. Viscosity prediction through ANFIS

The subsequent section encompasses two segments. First, an account of the proposed methodology's execution procedure within the MATLAB environment is delineated. Subsequently, the outcomes regenerated by applying the machine learning technique

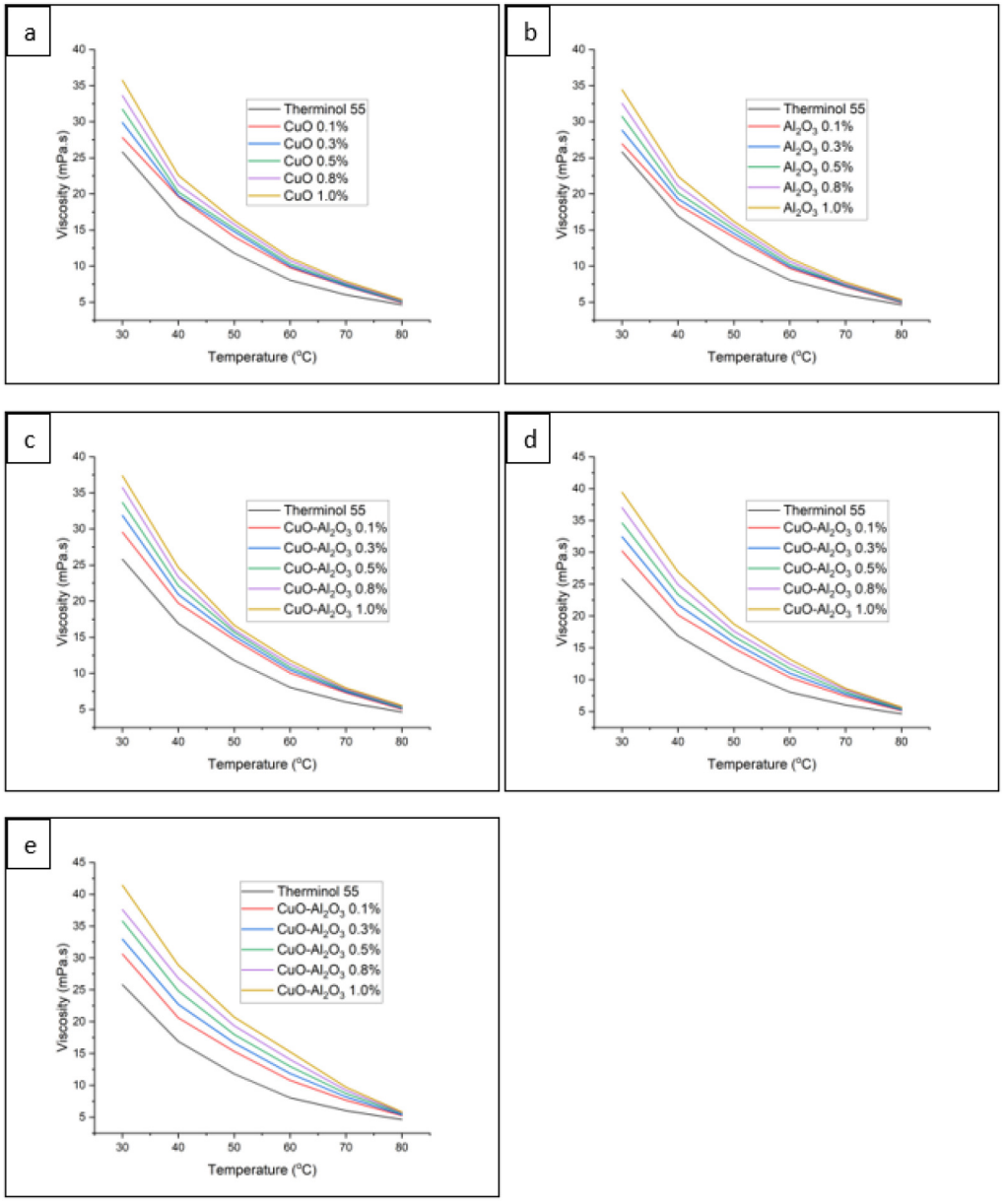


Fig. 2. a) Viscosity of CuO-Therminol 55 Nanofluid with Concentration 0.1 wt%, 0.3 wt%, 0.5 wt%, 0.8 wt%, and 1.0 wt%. b) Viscosity of Al_2O_3-Therminol 55 nanofluid with concentration 0.1 wt%, 0.3 wt%, 0.5 wt%, 0.8 wt% and 1.0 wt%. c) Viscosity of CuO-Al_2O_3 (10:90) Hybrid Therminol 55 Nanofluid with Concentration 0.1 wt%, 0.3 wt%, 0.5 wt%, 0.8 wt% and 1.0 wt%. d) Viscosity of CuO-Al_2O_3 (20:80) Hybrid Therminol 55 nanofluid with concentration 0.1 wt%, 0.3 wt%, 0.5 wt%, 0.8 wt% and 1.0 wt%. e) Viscosity of CuO-Al_2O_3 Hybrid (30:70) Therminol 55 Nanofluid with Concentration 0.1 wt%, 0.3 wt%, 0.5 wt%, 0.8 wt% and 1.0 wt%.

are scrutinized. This section provides insights into the system's behavior facilitated by the developed ANFIS.

3.2.1. Model development

To execute the proposed approach elaborated in the preceding section employing ANFIS, MATLAB software serves as the primary tool. The dataset comprises 180 data points, encompassing diverse configurations of temperature, concentration, and different portions of Al_2O_3-CuO. The temperature spans from 30 to 80 °C, while the concentration is from 0% to 1%. Additionally, compositions of 0:100, 10:90, 20:80, 30:70, and 100:0 for Al_2O_3-CuO are considered. Standardization of the dataset is imperative to maximize the accuracy of the proposed ANFIS during both the training and testing phases. Subsequently, the dataset is partitioned into 80% and 20% subsets for training and testing the proposed T2FNN. Notably, 144 of the 180 datasets are employed for

Table 1. The hyperparameters of three investigated models, including DT, SVR, and ANFIS.

Model	Hyperparameters
DT	Categorical Predictors = 3; Minimum Parent Size = 4; Maximum Number of Splits = 29
SVR	Kernel = Gaussian; KFold = 10
ANFIS	Number of Membership = 4; Epoch Number = 760; Initial Step Size = 1.2977×10^{-5}; Step Size Decrease Rate = 0.52257; Step Size Increase Rate = 1.0848.

training, while the remaining 36 are reserved for testing. In addition, decision tree (DT) and SVR are designed and developed to evaluate the proposed model's accuracy against the traditional machine learning methods. Table 1 shows the hyperparameters of the three investigated models (DT, SVR, and ANFIS) to reach the highest accuracy in predicting viscosity. Each hyperparameter plays a critical role in the learning process. The number of membership functions determines the model's granularity in capturing input-output relationships [42]. The epoch number controls the iterations for training, impacting convergence. Step size parameters influence how quickly or slowly the model adjusts weights, balancing convergence speed and accuracy.

3.2.2. Model analysis

Fig. 3 illustrates the distribution of errors in viscosity prediction by the proposed ANFIS model, utilizing 30 bins. The error histogram unveils a right-skewed distribution, with the highest frequency at 0.007756. Mean errors for the training, testing, and combined datasets are computed as 0.7027, 0.2130, and 0.6041, respectively. The provided error histogram with 30 bins visualizes the distribution of prediction errors generated by a model. The horizontal axis represents the error values, which range from approximately −2.62 to 5.85, indicating the magnitude of deviation between the predicted and actual values. The vertical axis displays the number of instances (frequency) that fall into each error bin. This type of visualization provides crucial insights into the model's performance, revealing how well the predictions align with the true values and where the largest discrepancies occur. The majority of errors are concentrated near zero, which is marked with a vertical yellow line labeled as Zero Error, indicating that most predictions are reasonably accurate. The highest frequency of errors occurs between −0.35 and 0.88, with the tallest bars in this region representing more than 15 instances per bin. This suggests that the model is generally reliable, with a high proportion of predictions having small errors close to zero [43]. However, the spread of errors to both the negative and positive sides of the zero line indicates that the model exhibits both underprediction and overprediction tendencies, though neither seems dominant [44]. On the left side of the histogram, negative errors extend to −2.62, showing that in some cases, the model significantly underpredicted the target values. These extreme negative errors, though limited in frequency, highlight instances where the model underestimated the actual values. Similarly, on the right side, positive errors reach as high as 5.85, indicating instances where the model overpredicted the target values by a large margin. These outliers suggest the presence of some complex data points that the model struggled to predict accurately, possibly due to data noise or limitations in the training set. The

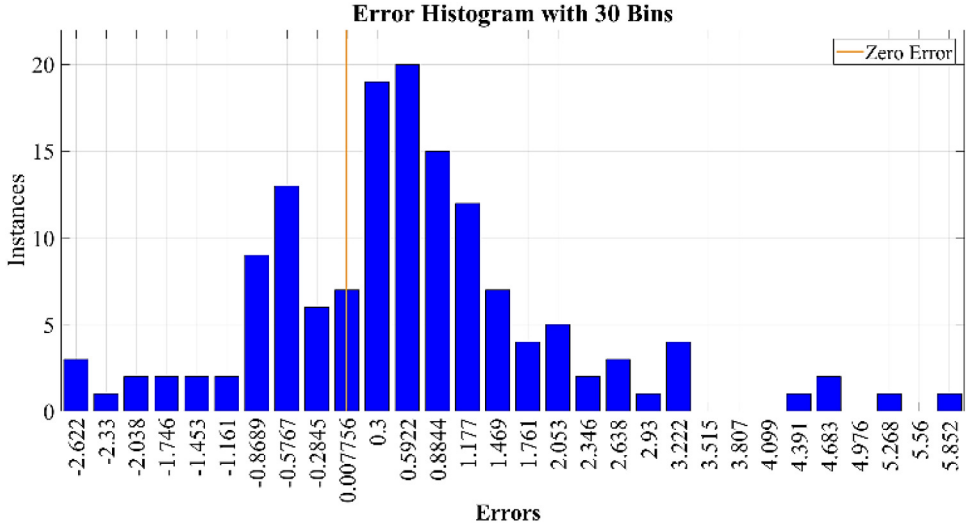


Fig. 3. The error histogram of ANFIS with the implementation of all data, including training and testing.

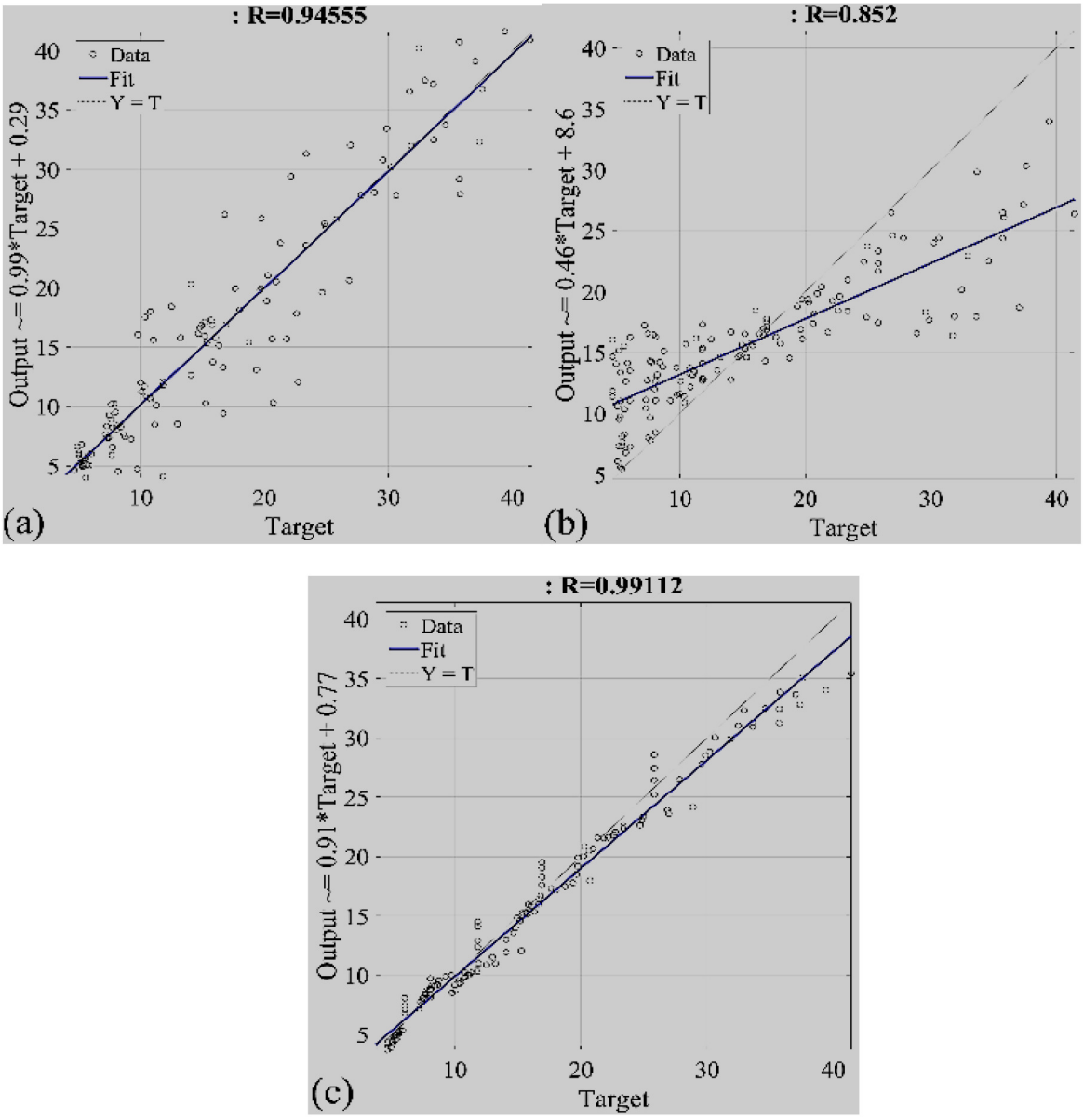


Fig. 4. The regression for all datasets with the implementation of (a): DT; (b): SVR; (c): ANFIS.

histogram's overall shape shows a slightly right-skewed distribution, meaning that the model tends to have more positive errors (overpredictions) than negative ones. This skew suggests that the model may require further fine-tuning or adjustment to handle certain scenarios more accurately and reduce over-prediction errors. Additionally, reducing the influence of outliers on both ends of the distribution could improve the model's generalization performance. The error histogram reveals a well-performing model with the majority of predictions close to zero error, but it also highlights opportunities for improvement. Addressing the outliers and reducing the spread of larger errors through hyperparameter optimization or additional data preprocessing could enhance the model's reliability and predictive power.

Fig. 4a-c depicts regression plots comparing experimental viscosity data with DT, SVR, and ANFIS by implementing all datasets and utilizing 30 bins. Based on the represented results, the R-value of DT, SVR, and ANFIS are 0.9456, 0.8520, and 0.9911, respectively. It proves the higher efficiency of ANFIS compared to traditional machine learning methods such as DT and SVR [45]. The three graphs represent the performance of three different models—Decision Tree (DT), Support Vector Regression (SVR), and Adaptive Neuro-Fuzzy Inference System (ANFIS)—in predicting a specific output based on a target value.

These models are compared based on their R-values, which are measures of how well the predicted output fits the actual target data. The Decision Tree model shows a strong correlation between the predicted output and the target value, with an R-value of 0.9456. This indicates that about 94.56% of the variance in the output can be explained by the target variable. The fit line equation Output $\approx 0.99 \times$ Target + 0.29 suggests that the model is nearly linear, with a slope close to 1 and a small intercept of 0.29. This model performs well in predicting the output values, but the spread of points around the fit line indicates some deviation from perfect prediction, particularly for higher target values. The Support Vector Regression model has an R-value of 0.8520, which is lower than the DT model, indicating that only 85.20% of the variance in the output can be explained by the target variable. The regression equation Output $\approx 0.46 \times$ Target + 8.6 suggests a much lower slope, indicating that the model underestimates the increase in output as the target value increases. The higher intercept of 8.6 shows that the model's predictions tend to start at a much higher baseline than the DT model. While SVR is a robust regression model, it may not perform as well in capturing the full relationship between the output and target for this particular dataset, as seen in the wider spread of points around the fit line.

The ANFIS model demonstrates the strongest correlation with an R-value of 0.9911, indicating that 99.11% of the variance in the output is explained by the target variable. The fit line equation Output $\approx$ $0.9 \times$ Target + 0.77 shows a slope close to 1, and the intercept is slightly higher than in the DT model but still relatively low. The close clustering of data points around the fit line and the near-perfect R-value suggests that ANFIS is the most accurate model for predicting the output values. This model captures both linear and non-linear relationships, making it particularly suited to complex data. The three models vary significantly in their ability to predict the target values accurately. The ANFIS model outperforms the other two, with an R-value close to 1, indicating near-perfect predictions. This result is expected, as ANFIS combines the strengths of neural networks and fuzzy logic to model complex relationships that may not be purely linear. The DT model also performs well, with an R-value of 0.9456, showing it can handle this dataset effectively. However, Decision Trees can sometimes struggle with overfitting, which might explain the small deviations seen at higher target values. This model is simple and interpretable, making it useful in certain scenarios where transparency is important, but its performance falls short of ANFIS in this case. SVR, on the other hand, performs the least well, with an R-value of 0.8520. Its lower slope and higher intercept suggest that the model has more difficulty in fitting the data, potentially due to the complexity of the relationships in the dataset. SVR is known for its robustness in handling small datasets and outliers, but in this context, it seems less capable of capturing the full variability in the target values compared to DT and ANFIS. ANFIS emerges as the best-performing model in this case, providing highly accurate predictions and capturing both linear and non-linear relationships within the data. The DT model also performs well but falls short of ANFIS in terms of precision. SVR, while a powerful model in certain contexts, does not perform as well with this dataset, leading to a lower R-value and less accurate predictions.

Fig. 5a-c presents experimental (Target) and predicted (Output) viscosity by investigating machine learning models during the testing phase. These plots facilitate the evaluation of the accuracy of ANFIS predictions against experimental data compared to those of DT and SVR. In Fig. 5a, the mean squared error (MSE) and RMSE between experimental and predicted viscosity via DT for the testing samples are computed as 31.69 and 5.6293. Similarly, Fig. 5b illustrates the MSE and RMSE values of 46.92 and 6.8495, predicted viscosity via SVR for the testing samples. Finally, Fig. 5c shows that the MSE and RMSE values of predicted viscosity via ANFIS are 1.06 and 1.0278. It proves the lower MSE of ANFIS compared with DT and SVR, with 96.67% and 97.75%, respectively. Also, RMSE using ANFIS decreased by 81.74% and 84.99% compared with DT and SVR, respectively. ANFIS demonstrates the closest agreement between the target and predicted values, as seen by the near-perfect overlap of the data points in most of the trials. The red asterisks representing the predicted values are nearly indistinguishable from the target values, showing that the ANFIS model has excellent predictive capabilities. This is further supported by the high R-value of 0.9911 from the earlier linear regression plot, which indicates that 99.11% of the variance in the output is explained by the target data. The ANFIS model can capture both linear and non-linear relationships effectively, making it highly suitable for this type of complex prediction, especially when dealing with experimental viscosity data that may exhibit non-linear behavior. Although the DT model has a decent R-value of 0.9456, this plot shows more significant deviations between the predicted and target values compared to ANFIS. In particular, the predicted values sometimes underestimate or overestimate the experimental viscosity in certain trials. The gaps between the red and blue points indicate that while the DT model performs

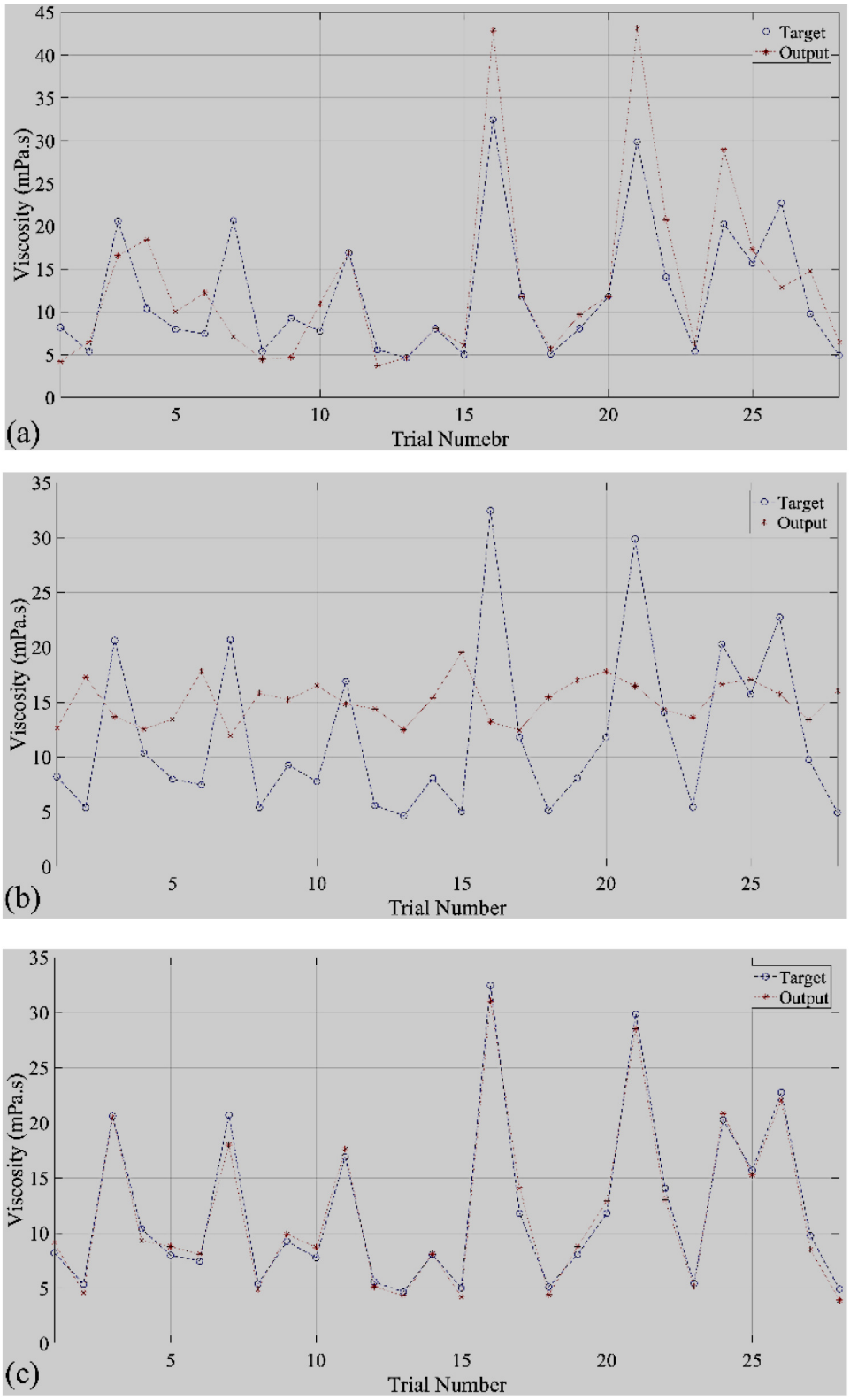


Fig. 5. The experimentally (Target) and computationally (Output) extracted viscosity via (a): DT; (b): SVR; and (c): ANFIS.

reasonably well, it is not as precise as ANFIS. Decision Trees are known for their simplicity and interpretability but may not be able to handle the complexity and subtle non-linear patterns in the dataset as effectively as ANFIS can.

Another problem with this model may be that it is unable to cope with the sharp increase in viscosity that can be viewed around the 15th–20th trials, which results in greater divergences between the data in the predicted and validation data set. Thus, the assumption that the differences between the predicted and estimated data may also be larger can be considered justified. The outcomes can be defined as fairly consistent. Notably, there is a far greater divide between the predicted and actual value by an average of 0.8520 R-value. Looking at the graph, regression lines continue to be above or below the line, depending on the overall amount of difference in viscosity. As seen in this case, the SVR model lacks the flexibility necessary to address variations in experimental data, confirming earlier suggestions concerning the trials whose graphs feature sharp peaks and bottom lines. When looked at more closely, however, the range can be considered well out of the study's scope. The possibility that SVR is not particularly effective with such datasets as the ones previously described could also be considered. The results are coherent with the described assumption since the data varies and is very far from being classified as linear. Generally, SVR is most effective when the set of data is small, or the object follows a simple trend; the data present is too intricate for the model, leading to a high percentage of errors. Overall, it is clear from the data that the ANFIS model tops both, DT and SVR, in terms of accuracy and reliability.

In contrast, the Decision Tree model, while reasonably accurate, exhibits more noticeable deviations, particularly at higher viscosity values or when the viscosity changes rapidly between trials. The simplicity of DT makes it a valuable tool for certain applications, but its limitations become apparent when dealing with complex, fluctuating data like viscosity. SVR, on the other hand, performs the worst among the three models. Its lower R-value and the visible discrepancies in the graph indicate that it cannot handle the non-linear patterns in the viscosity data as effectively as ANFIS or even DT. SVR may work better for datasets with fewer fluctuations and a clearer linear trend, but in this context, it falls short. ANFIS model stands out as the most effective tool for predicting viscosity in this dataset, offering near-perfect alignment with the experimental data. The Decision Tree model provides a decent alternative but with less accuracy, while the SVR model performs the least effectively in this case.

3.2.3. Data interpretation

Fig. 6a-c shows the rule surface of the extracted T2FNN in calculating viscosity based on arrangements of the input process parameters, including temperature, concentration, and Al_2O_3-CuO portion. To be specific, Fig. 6a shows the viscosity variation based on the different arrangements of temperature and concentration. Based on the represented results, the highest viscosity = 34.27 (mPa.s) reaches with temperature = 32.63 (°C) and concentrations = 1% or 0.01. It can be concluded that the highest viscosity appears at lower temperatures with higher concentrations [36, 46]. Fig. 6b shows the viscosity variation based on the different temperatures and Al_2O_3-CuO portion arrangement. As in Fig. 6a, the lower temperature can reach the highest viscosity. However, the portion arrangement of Al_2O_3-CuO does not show the linear behavior on viscosity. The highest viscosity = 34.34 (mPa.s) reaches with temperature = 32.63 (°C) and portion = 30:70 between CuO and Al_2O_3. However, 2 local optimal points for different portions in temperature = 32.63 (°C), including 23.68:76.32 and 12.63: 87.37 between CuO and Al_2O_3. Fig. 6c shows the viscosity variation based on the different concentrations and Al_2O_3-CuO portion arrangement. Higher viscosity reaches higher concentrations and Cu portions until 30 out of 100. However, one local optimal point at concentration = 1% or 0.01 and portion = 23.68:76.32 between CuO and Al_2O_3 with viscosity = 14.74 (mPa.s), as observed in Fig. 6b. The concentration of the nanoparticles is varied between 0.001 and 0.008, while the temperature ranges from 30°C to 70°C. The surface shows a clear trend: as the temperature increases, the viscosity decreases. This behavior is expected, as viscosity generally reduces with an increase in temperature due to the reduction in intermolecular forces, which allows the fluid to flow more easily. This pattern is also consistent across different concentrations, with the higher concentrations resulting in higher viscosities.

The interaction between concentration and viscosity shows that as concentration increases, the viscosity increases as well. This is because a higher concentration of nanoparticles in the base fluid creates more resistance to flow, increasing the viscosity. Thus, at lower temperatures and higher concentrations, viscosity reaches its highest values, whereas, at higher temperatures and lower concentrations, it is at its minimum. The temperature still ranges from 30°C to 70°C, and the portion of Cu varies between 0 and 30%. Similar to the first graph, viscosity decreases as the temperature rises. However, the portion of Cu seems to have a more complex relationship with viscosity. At lower temperatures, viscosity peaks when the Cu portion is between 10% and 20%. This might

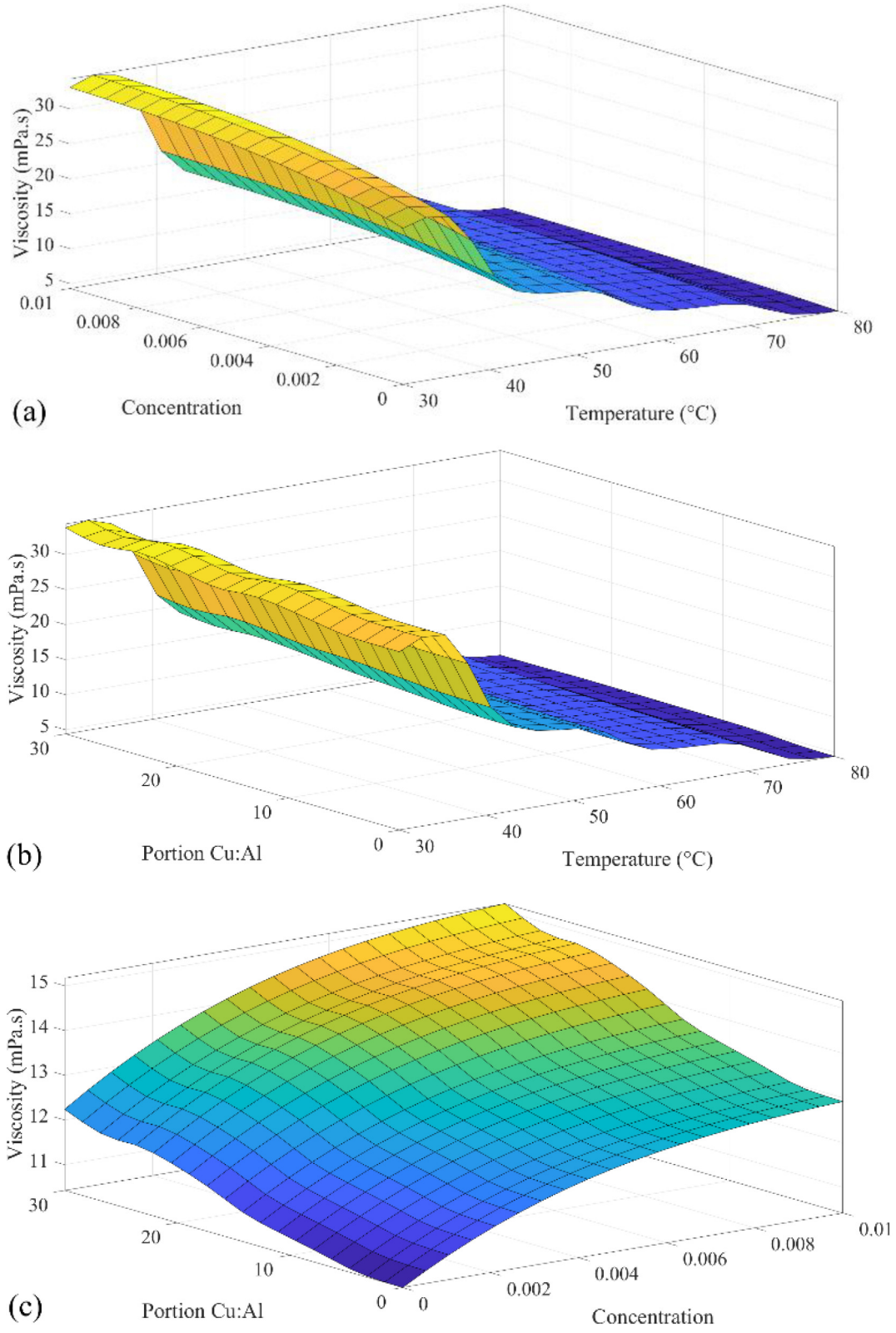


Fig. 6. ANFIS rule surface for calculation of viscosity (mPa.s) based on: (a) temperature (°C) and concentration (%); (b) temperature (°C) and Cu: Al portion; (c) concentration (%) and Cu: Al portion.

be due to the particular thermal conductivity and mechanical properties of the hybrid nanoparticles. Copper is known for its high thermal conductivity, while aluminum offers lighter mass and distinct material properties. When mixed in an optimal ratio, the hybrid nanoparticles enhance the heat transfer properties, affecting the viscosity in a non-linear fashion. At higher temperatures, the variation in Cu ratio has a smaller effect on viscosity, which suggests that temperature becomes the dominant factor in determining the viscosity at elevated levels. The portion of Cu and concentration significantly impact viscosity. As concentration increases, viscosity rises, as expected, due to the increasing number of nanoparticles interacting with the fluid molecules. Additionally, the portion of Cu also contributes to changes in viscosity, with an optimal range between 10% and 20% Cu producing the highest viscosity. Beyond this range, the effect on viscosity diminishes slightly.

The presence of copper nanoparticles, which have superior thermal and electrical properties, combined with aluminum, creates an ideal hybrid nanofluid that maximizes viscosity at particular concentrations. At lower concentrations, the effects of the Cu portion on viscosity are minimal, but at higher concentrations, the impact becomes more pronounced, especially around the optimal Cu ratio. The three rule surfaces provide a comprehensive view of how the process parameters (temperature, concentration, and Cu portion) influence the viscosity of Al_2O_3-CuO nanofluid. Temperature appears to be the most dominant factor, as viscosity consistently decreases with increasing temperature across all surfaces. Concentration is the second most influential factor, with higher concentrations leading to higher viscosities. The portion of Cu nanoparticles also plays a significant role, with an optimal ratio leading to maximum viscosity at specific points, particularly at lower temperatures and higher concentrations. The non-linear interactions between these parameters are well captured by the T2FNN model, highlighting its ability to account for the complex, fuzzy relationships inherent in nanofluid systems. This type of modeling approach is essential for optimizing the performance of nanofluids in heat transfer applications, as it provides insights into the ideal combinations of temperature, concentration, and nanoparticle composition for achieving desired viscosity characteristics. These findings could help in fine-tuning nanofluids for specific industrial applications, such as cooling systems or energy storage systems, where viscosity directly impacts efficiency and performance.

The concentration ranges examined vary from 0.1% to 1%. In the lower concentration range (0.1% to 0.4%), viscosity remains relatively low, particularly at higher temperatures. This is because a smaller number of nanoparticles are suspended in the fluid, resulting in fewer interactions between the particles and the fluid molecules, thereby reducing resistance to flow. This lower viscosity may be advantageous in applications that require better flow characteristics, such as efficient pumping or systems where fluid movement needs to be rapid. However, the lower concentration also reduces the thermal conductivity and heat transfer performance of the nanofluid, making it less suitable for applications where these properties are critical. In contrast, in the higher concentration range (0.4% to 1%), the viscosity increases significantly. This is due to the larger number of nanoparticles, which enhance particle-particle and particle-fluid interactions, creating greater resistance to flow. This higher viscosity can improve the heat transfer efficiency in systems where improved thermal properties are required, such as cooling systems or energy storage applications. However, too high a viscosity may introduce challenges, such as increased pumping power and reduced fluid flow. Therefore, the optimal concentration range would depend on balancing the need for improved thermal properties with manageable viscosity levels, typically around 0.4% to 0.8%, where viscosity is moderate but still conducive to enhanced thermal performance.

4. Conclusions

This study demonstrates the effectiveness of the Adaptive Neuro-Fuzzy Inference System (ANFIS) in accurately predicting the viscosity of hybrid alumina-copper oxide nanofluids. The proposed model achieved a Root Mean Square Error (RMSE) of 1.0278 and an R-value of 0.9911, significantly outperforming traditional models such as Decision Trees (DT) and Support Vector Regression (SVR), whose RMSE values were 96.67% and 97.75% higher, respectively. These results underscore ANFIS's superior predictive capability and its ability to handle nonlinear and complex relationships. The findings highlight the potential of hybrid nanofluids in enhancing heat transfer efficiency, particularly in medium-temperature applications, while promoting sustainable engineering practices. Future work should explore a broader range of nanoparticle compositions and fluid dynamics to extend the applicability of the model across diverse industrial conditions.

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Conflicts of interest

The authors declare no conflicts of interest.

Data availability

Data will be available on a reasonable request from the corresponding author.

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