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ANN Application Of Machine Learning For Evaluating Thermophysical Properties Of Hybrid Nanofluids: A Review

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Abstract: The utilization of machine learning methods for modelling the thermophysical properties of hybrid nanofluids has gained substantial attention due to its potential to enhance prediction accuracy and versatility. This study provides all-encompassing analysis of the diverse methods employed in predicting dynamic viscosity and thermal conductivity of hybrid nanofluids. In recent times, intelligence-based models have emerged to predict these essential properties of hybrid nanofluids, therefore artificial neural network is discussed from simple correlation to complex. Optimization algorithm, input factors and training functions significantly influence the reliability of prediction. Furthermore, alternative methodologies like adaptive Nero-fuzzy inference system and support vector machines are explored. The current review emphasizes the importance of advancing these models by embracing a wider array of input factor and considering novel optimization techniques with the goal of creating predictive models that are both accurate and adaptable across diverse hybrid nanofluid scenarios.

Keywords: ANN • Dynamic Viscosity • Hybrid Nanofluids • Machine Learning • Thermal Conductivity

Introduction:

Nanotechnology offers the potential to enhance system performance and acquire materials with superior attributes in various scientific domains Ramezanizadeh et al (2019). Nanofluids consist of a blend of liquid known as the base fluid and solid nanoparticles in the nano size range and address limitations in heat transfer efficiency observed in conventional heat transfer fluids Mostafa et al (2020). The improved thermophysical properties exhibited by these fluids with their elevated thermal conductivity, position them as the preferred choice for incorporation into heat transfer devices and systems for thermal managements Nazir et al (2019). Despite increased thermal conductivity, the inclusion and settling of solid particles leads to increase in their dynamic viscosity. In general, the thermophysical characteristics of NFs depend on various factors like properties of the base fluid (BF) concentration, temperature, solid particle shape among others Wang et al (2021).

In prior research, conventional NFs featured an independent material dispersed within the base fluid, similar to conventional nanofluids. Researchers, like Leticia et al. Letícia et al (2019) evaluated thermal conductivity and viscosity within EG-based NFs with diamond/silver nanostructures with temperature and concentration ranges from (10°C-60°C) and (0%-0.1%) respectively. The result showed that the highest thermal conductivity enhancement occurred at 60°C and 0.1% concentration. Trinh et al (2018) explored the impact of temperature on thermal conductivity of graphene-carbon nanotube HNF in ethylene glycol. The result showed that the specified hybrid nanostructure at volume fraction of 0.07% within the BF resulted in significant improvements in thermal conductivity. Asadi (2018) assessed the dynamic viscosity of oil-based nanofluid containing MWCNT/ZnO nanostructure with

temperature range from (15°C-55°C) and concentration from (0.125-1%). They observed that viscosity decreases and improved heat transfer coefficient with increasing temperature.

The experimental measurements of thermal conductivity and dynamic viscosity in HNF is both time-consuming and challenging. To address this, numerous predictive models have been formulated and relying on factors like algorithm choice, input variables and quantity of data points Zendehboudi and Li (2017). Among the assortment of available techniques, machine learning (ML) approaches have found widespread adoption in domain. Particularly noteworthy the application of artificial neural network (ANN) renowned for their accuracy and precision. Alongside ANN models, other methodologies like support vector machines (SVM) have demonstrated promising capabilities in suggesting NFs properties. The present paper endeavours to provide an all-encompassing review of prior investigations concerning the utilization of ML methods for modelling dynamic viscosity and thermal conductivity in hybrid nanofluids.

Nomenclature:

ANN: Artificial Neural Network	ML: Machine Learning
ANFIS : Adaptive Neuro-Fuzzy Inferences System	MWCNT: Multi Walled Carbon Nano Tube
BF: Base Fluid	NFs: Nanofluids
HNF: Hybrid Nanofluid	RBF: Radial Basis Function
LSSVM: Least Square Support Vector Machine	SVM: Support Vector Machines
LS-SVR: Least Square Support Vector Regression	SWCNT: Single Walled Carbon Nano Tube
MLP: Multilayer Perceptron	

Methodology Employed in the Investigation:

To conduct a detailed review, various steps were taken. In step 1: scientific database was undertaken encompassing platforms such as Science Direct, Scopus and Google Scholar. Step 2: Relevant documents were sought using keywords including HNF, Thermal Conductivity, Dynamic Viscosity, ML and ANN and some methods. Step 3 categorized the advanced collection into studies on thermal conductivity and dynamic viscosity. In step 4: After outlining the article structure including its divisions and subdivisions the collected data from this review was methodically organised and integrated into relevant sections. The overall procedure of this review study is visually depicted in Figure 1.

Fig. 1. The Methodology Employed in the Current Review Study

Most Relevant Methods of Machine Learning:

As previously indicated, there exist numerous machine learning methods for modelling and forecasting the performance of engineering systems Maleki et al (2021). Within this array of methods, the MLP-ANN, ANFIS, LS-SVM and the radial basis Function (RBF) ANN have found extra extensive applications in modelling nanofluid properties. In the ensuing subsections, we explore into those approaches that are most pertinent to the objectives.

Artificial Neural Network Employing a Multilayer Perceptron Architecture:

The foundation of an ANN is rooted in the amalgamation of intelligent computational techniques with biological systems. Among the prominent variations of ANN, the multilayer perceptron (MLP) stands out as one of the most extensively employed. The configuration of MLP is visually elucidated in fig. 1. The MLP consist of nodes across three layers: input, hidden and output. The number of hidden layers can vary based on the problem complexity. Each node employs weight vector to establish connections with nodes in the subsequent layer Zendehboudi and Li (2017). In the networks initial layer, the nodes are added and employed as inputs for the subsequent layer. If we denote the model input as vector x and n_j as the input of the j^{th} node in the subsequent layer:

$$n_j = \sum_{i=1}^{n} \omega_{ji} x_i + \theta_j \qquad j = 1, 2, \ldots\ldots k \qquad (1)$$

In equation (1), k represents the count of nodes, θ_j denotes the level of the j^{th} hidden node and ω_{ji} represents the weight of connection to that node. Subsequently, the function f is employed to process and arrange the collective inputs for the subsequent layer leading to:

$$y_j = f(n_j) = f\left(\sum_{i=1}^{n} \omega_{ji} x_i + \theta_j\right) \qquad j = 1, 2, \ldots\ldots k \qquad (2)$$

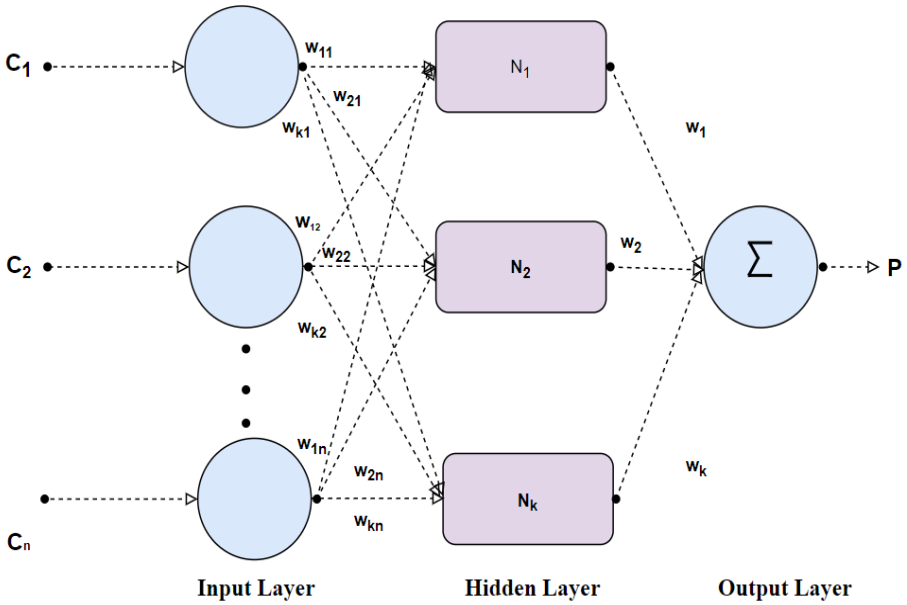

Fig. 2. Structure of Multilayer Perceptron-ANN.

These functions exhibit distinct characteristics and can be joined across various approaches. By scaling the concealed layer output using linking weight derives node output. The count of inputs corresponds to the number of neurons in the input layer. However,

standardized methodology for determining the size and quantity of hidden layers is absent and they depending on factors like problem intricacy and dataset distribution Panchal et al (2011). As the training process unfolds iteratively neurons are incrementally incorporated to attain an optimal state. In constructing predictive models using MLP, the training phase is crucial and involving bias and weight values adjustments. The widely used backpropagation (BP) algorithm fine-tune bias and weight values during the training phase of MLP, and integral process in constructing neural networks.

Modelling Thermal Conductivity Through Machine Learning Approaches:

$$\frac{k_{nf}}{k_{bf}} = 0.006(\varphi^{1.090})T^{1.051} + 1.014 \quad (3)$$

$$\frac{k_{nf}}{k_{bf}} = 4.055\left(\left(\frac{\varphi}{34}\right)^{1.09}\right) exp\left(\frac{T}{34}\right) + 1.013 \quad (4)$$

The coefficient of determination for these double correlations at 0.99 respectively. In these equations k_{nf} represent the thermal conductivity of NFs and k_{bf} represents the thermal conductivity of BF, while T and φ in equation (3) and (4) indicate the nanofluid temperature and volume fraction. The variable coefficient within the correlations can enhance the comprehensiveness. Rostami et al. Rostami et a*l* (2021) compared the effectiveness of correlations and ANN in predicting the thermal conductivity of CuO-SWCNT/ethylene glycol NF. The result revealed that the highest absolute deviations for correlation and ANN at 5.4% and 0.5% respectively. Visualize in figure 2, the projected values derived from ANN were notably closer to the actual values, underscoring its superiority over correlation. Esfe et al (2017) used both ANNs and correlation techniques to model the thermal conductivity of $SWCNT - Al_2O_3/EG$ nanofluid. The result revealed that ANNs were employed for modelling deviation reduced to 1.93%. Hemmat et al (2018) assessed the

Recent years have seen significant focus on the modelling of thermal conductivity in NFs. Mathematical correlations are favoured for computational efficiency and ease to use, although they may not always provide high accuracy. Akhgar and Toghraie (2018) formulated a relationship to forecast the thermal conductivity of $TiO_2 - MWCNT$ / H_2O -EG mixtures providing means to approximate thermal conductivity for certain HNF. Within their investigation, they put forward two correlations employing temperature and concentration of solid nanostructures and employed curve fitting to express them as:

reliability of RBF and MPL for modelling the thermal conductivity of HNF comprising MWCNT alongside other oxide particles Al_2O_3 and TiO_2 . They found that the utilization of GMDH yielded the most precise forecasts and achieving coefficient of determination range from (0.96-0.98) depending on the hybrid nanostructure. Shahsavar et al (2025) explored the SVM's superiority over LS-SVR for graphene oxide-silicon carbide/water NFs, while ANFIS offers additional opportunity for precise HNF thermal conductivity.

Utilizing Machine Learning Techniques for the Prediction of Dynamic Viscosity:

The dynamic viscosity of NFs significantly impacts on fluid flow dynamics, especially pressure loss and heat transfer capabilities. Understanding its role in influencing reynolds and nusselt number is crucial for addressing thermal engineering issues. Rashmi and Vikash (2020) introduced a correlation derived from the experimental measurements for model the dynamic viscosity of $Cu - Al_2O_3 - TiO_2$ / H_2O NFs. The

formulated correlation for the NFs was presented in the subsequent manner:

$$\mu_{nf} = \mu_{bf}\left(0.955 - 0.00271 * T + 1.858\frac{\varphi}{100} + \left(705\frac{\varphi}{100}\right)^{1.223}\right) \quad (5)$$

Relative to correlations established through curve fitting, the modelling of dynamic viscosity in HNF can achieve greater precision by employing ANN. Amin et al (2021) utilized both LS-SVM and correlation methods predicted dynamic viscosity of HNF with LS-SVM exhibit superior performance due to its improved precision. Notably, R-squared values for the regression outcomes were 0.9 for both correlation and LS-SVM. The graphical representation in Figure 3 demonstrates that the optimized ANN yielded improved agreement between the calculated values and empirically measured results. Notably, the extreme pure deviations were approximately 4.5% and 1.6% when employing correlations and ANN, respectively.

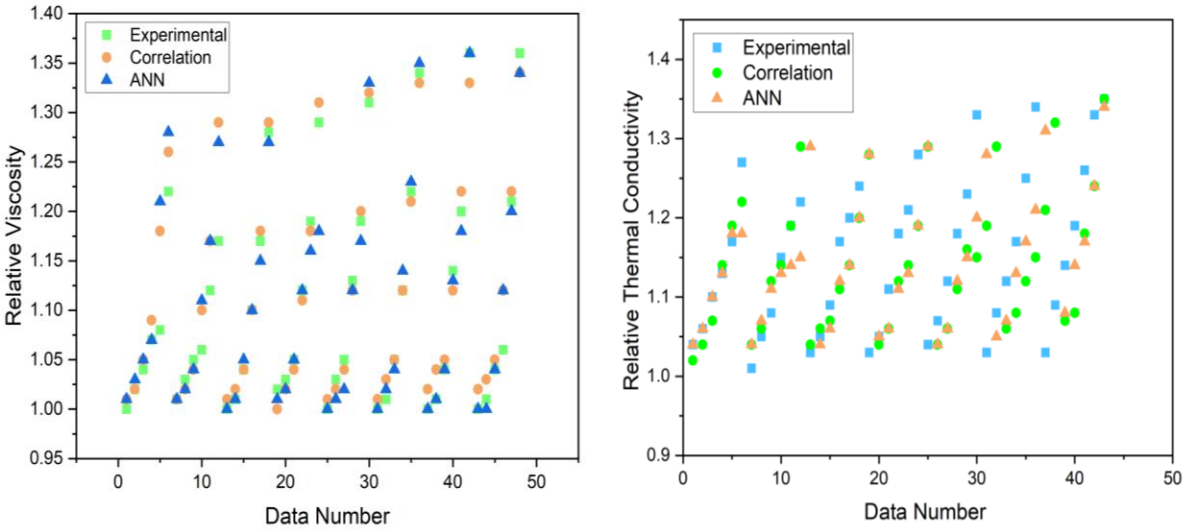

Fig. 3. (a) Comparison between predicted thermal conductivity through correlation and ANN; (b) Comparison between predicted dynamic viscosity through correlation and ANN.

Conclusion: This review article focuses on the applications of diverse data-driven techniques for evaluating dynamic viscosity and thermal conductivity in hybrid nanofluids. the principal conclusion distilled from the surveyed literature is outlined as:

- The construction of ANN models and the selection of training and transfer functions play pivotal roles in ensuring the reliability of predictions.
- In additions to ANNs another data-driven method such as ANFIS and SVM exhibit the capability to construct analytical models for properties of HNF.
- Advanced techniques like ANNs exhibit superior predictive capabilities. Also, the Reliability of these models depends on meticulous architecture design, appropriate training and transfer functions and efficient optimization algorithms.

Future Recommendations: The following points outline potential avenues for future advancement in Machine Learning Applications for Modelling Thermophysical Properties of Hybrid Nanofluids

- Expand input variables beyond nanofluids composition to include BF properties, nanostructures attributes and broader experimental data. This expansion will lead to the development of models that are both versatile and highly accurate.

- Explore innovative optimization techniques alongside conventional methods to improve prediction accuracy and minimize errors during network training.
- Investigate the computational efficiency and precision of several training functions in ANN to optimize training processes and enhance model performance.

References:

Akhgar A, and Toghraie D (2018). An experimental study on the stability and thermal conductivity of water-ethylene glycol/TiO2-MWCNTs hybrid nanofluid: Developing a new correlation, *Powder Technology*, 338: 806–818.

Asadi A (2018). A guideline towards easing the decision-making process in selecting an effective nanofluid as a heat transfer fluid', *Energy Conversion and Management*, 175: 1–10.

Asadi A et al. (2021). Feasibility of least-square support vector machine in predicting the effects of shear rate on the rheological properties and pumping power of MWCNT–MgO/oil hybrid nanofluid based on experimental data, *Journal of Thermal Analysis and Calorimetry*, 143(2): 1439–1454.

Esfe M H et al. (2017). Estimation of thermal conductivity of ethylene glycol-based nanofluid with hybrid suspensions of SWCNT–Al2O3 nanoparticles by correlation and ANN methods using experimental data, *Journal of Thermal Analysis and Calorimetry*, 128(3): 1359–1371.

Esfe H M, Esfandeh S and Rejvani M (2018). Modeling of thermal conductivity of MWCNT-SiO2 (30:70%)/EG hybrid nanofluid, sensitivity analyzing and cost performance for industrial applications: An experimental based study, *Journal of Thermal Analysis and Calorimetry*, 131(2): 1437–1447.

Maleki A et al. (2021). Applying different types of artificial neural network for modeling thermal conductivity of nanofluids containing silica particles, *Journal of Thermal Analysis and Calorimetry*, 144(4): 1613–1622.

Shadloo M S, Maleki A and Shahrestani M I (2020). Numerical Investigation of Forced Convective Heat Transfer and Performance Evaluation Criterion ofAl2O3/Water Nanofluid Flow inside an Axisymmetric Microchannel, *Symmetry*, 12: 120.

Nazir H et al. (2019). Recent developments in phase change materials for energy storage applications: A review, *International Journal of Heat and Mass Transfer*, 129: 491–523.

Oliveira L R de et al. (2019). Experimental study on the thermal conductivity and viscosity of ethylene glycol-based nanofluid containing diamond-silver hybrid material, *Diamond and Related Materials*, 96: 216–230.

Panchal G et al. (2011). Behaviour Analysis of Multilayer Perceptronswith Multiple Hidden Neurons and Hidden Layers, *International Journal of Computer Theory and Engineering*, 332–337.

Ramezanizadeh M et al. (2019). Experimental and numerical analysis of a nanofluidic thermosyphon heat exchanger, *Engineering Applications of Computational Fluid Mechanics*, 13(1): 40–47.

Rostami S et al. (2021). Measurement of the thermal conductivity of MWCNT-CuO/water hybrid nanofluid using artificial neural networks (ANNs), *Journal of Thermal Analysis and Calorimetry*, 143(2): 1097–1105.

Sahoo R R and Kumar V (2020). Development of a new correlation to determine the viscosity of ternary hybrid nanofluid, *International Communications in Heat and Mass Transfer*, 111: 104451.

Shahsavar A et al. (2019). Robust Weighted Least Squares Support Vector Regression algorithm to estimate the nanofluid thermal properties of water/graphene Oxide–Silicon carbide mixture, *Physica A: Statistical Mechanics and its Applications*, 525: 1418–1428.

Trinh V P et al. (2018). Experimental study on the thermal conductivity of ethylene glycol-based nanofluid containing Gr-CNT hybrid material, *Journal of Molecular Liquids*, 269: 344–353.

Wang X et al. (2021). A comprehensive review on the application of nanofluid in heat pipe based on the machine learning: Theory, application and prediction, *Renewable and Sustainable Energy Reviews*, 150: 111434.

Zendehboudi A and Li X (2017). Modèles prédictifs robustes pour estimer le dépôt de givre sur des surfaces parallèle et horizontale, *International Journal of Refrigeration*, 80: 225–237.