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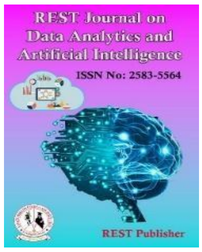

A Predictive Approach for Evaluating Thermo-Physical Properties of Nano fluids Using Artificial Intelligence Algorithms

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Abstract*: Artificial Intelligence (AI) algorithms are increasingly being employed as substitutes for conventional methods or as components within integrated systems. They have demonstrated effectiveness in addressing complex applied problems across various domains, gaining popularity in the present context. AI approaches exhibit the ability to learn from patterns, tolerate faults by handling noisy data, and manage non-linear problems. Once trained, they excel in generalization and fast estimation. This survey presents a comprehensive review of AI algorithms developed for investigating nanofluid-related issues. In nanofluid research, the most commonly used neural network model is Multilayer perceptron neural network (MLP), while the Radial Basis Function Neural Network (RBF-ANN) is the preferred training method. the Generalized Regression Neural Networks (GRNNs) exhibit a simple structure that reduces learning time, making them particularly suitable for nanofluids modelling. Consequently, for nanofluids with a large number of samples, the use of RBF-ANN is recommended. The findings demonstrate the substantial potential of ANN methods as predictive and optimization tools for nanofluids. This paper highlights the recent researches done for evaluating thermo-physical properties of nanofluids using AI algorithms.*

Keywords: *AI: Artificial Intelligence, ANN: Artificial Nural Network, RBF-ANN: radial basis function neural network, GRNN: generalized regression neural networks, MLP: Multilayer perceptron neural network.*

1. INTRODUCTION

Nonmaterial's have demonstrated considerable potential in diverse engineering domains [1,2]. The incorporation of nanoparticles, with dimensions ranging from 1 to 100 nm, into a base fluid during heating and cooling processes represents a viable approach for enhancing the overall heat transfer coefficient between the fluid and the adjacent surfaces [3,4]. Nanofluids have emerged as a contemporary and captivating category of nanotechnology-based heat transfer fluids, exhibiting substantial advancements over the past two decades. They demonstrate notably enhanced thermal conductivity and superior convective heat transfer characteristics in comparison to conventional fluids [5-7]. Consequently, nanofluids have garnered significant attention from researchers who seek to explore their potential in addressing the challenges posed by cooling technology and thermal management [8-9]. The thermal conductivity of ethylene glycol-based silicon carbide (SiC/EG) and water-based silicon carbide (SiC/DW) was measured and it was observed that SiC/DW NFs and SiC/EG NFs showed increment in thermal conductivity by 25 and 16%, respectively at 5 vol.% when compared with base fluids [10]. In the context of nanofluids, a considerable number of review articles have emerged over the past decade, comprehensively investigating diverse facets of their utilization in various applications. These applications encompass areas such as electronic cooling, solar systems, heat exchangers, microchannel systems, refrigeration applications, and phase change materials (PCMs) [11] and many researchers used Artificial Intelligence (AI) algorithm to predictive properties of nanofluids [12-17]. The neologism "artificial intelligence" was first introduced in 1956 by John McCarthy, a distinguished professor from the Massachusetts

Institute of Technology (MIT), who coined the term for the purpose of an academic conference convened during the same year. The inaugural AI program, Logic Theorist, which was showcased at the Dartmouth Conference, demonstrated its capability in proving mathematical theorems [18]. At present, AI research has diversified into several intriguing domains, prominently encompassing expert systems, neural networks, and robotics [19]. Nanotechnology encounters inherent physical constraints within its operational scale, wherein the governing principles diverge markedly from the macroscopic realm [11,18]. The estimation of thermal, kinematic and physical properties is very complex, time consuming and resource consuming process. Consequently, the accurate interpretation of outcomes derived from systems or devices at this nanoscale constitutes a prominent challenge confronting the field of nanotechnology. Various artificial intelligence tools that can be used for modelling and prediction of thermal, kinematic and physical properties of nanofluids are artificial neural network (ANN), fuzzy logic, computational fluid dynamics (CFD), ant colony optimization (ACO) algorithm, adaptive network-based fuzzy inference system (ANFIS) etc. For example, ML was used for modelling the dynamic viscosity of nanofluids [20] and artificial neural network (ANN) was used to predict the thermal properties of nanofluids, for various applications in cooling and renewable energy [21].

2. MACHINE LEANING (ML) TECHNIQUES IN NANOTECHNOLOGY

Nanofluids exhibit highly intricate thermophysical characteristics and are extensively utilized in intricate heat exchange processes and energy systems. Their impact on heat transfer, fluid dynamics, optical properties, and radiative performance demonstrates nonlinear behaviour. Consequently, the application of machine learning (ML) techniques becomes pertinent in nanofluid research. Several ML methodologies, including artificial neural networks (ANNs) such as the multi-layer perceptron artificial neural network (MLP-ANN) and radial basis function artificial neural network (RBF-ANN), group method of data handling (GMDH), adaptive neuro-fuzzy inference system (ANFIS), category and regression tree (CART), random forest (RF), and support vector machine (SVM) including the least-square support vector machine (LS-SVM), have been investigated. Additionally, these ML approaches can be effectively combined with metaheuristic algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), and imperialist competitive algorithm (ICA) to further enhance prediction accuracy and computational efficiency [22]. Artificial neural network Artificial Neural Networks (ANNs) stand out as the foremost and widely adopted algorithms in the realm of artificial intelligence [23]. They are favoured due to their favourable learning capabilities, especially in handling non-linear processes based on input patterns. Additionally, ANNs possess the capacity to learn diverse models, making them a viable alternative to complex analytical correlations. As a result, employing ANNs in numerical simulations significantly reduces both computation volume and time. The foundational structure of ANNs is inspired by the brain, comprising a collection of interconnected processing units, akin to the neural network's basic components. ANN has four types of algorithms as shown in figure 1 [24].

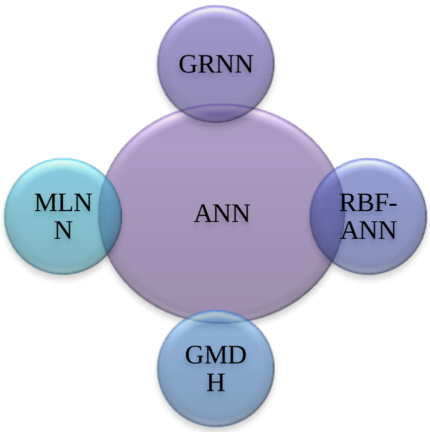

FIGURE1. Artificial neural network algorithms

2.1 Group method of data handling algorithm (GMDH): The GMDH technique was originally introduced by Ivakhnenko (1971) as a multivariate approach for modelling and recognizing intricate systems [25]. It operates as a self-organizing algorithm, generating complex models by evaluating their performance on a set of multi-input, single-output data patterns. The fundamental concept behind GMDH involves creating a theoretical function within a feed-forward network, utilizing a quadratic node transfer function with coefficients determined through regression. This process results in a model represented by interconnected neurons, employing quadratic polynomials within each layer, and generating new neurons in subsequent layers. This phenomenon enables the mapping of inputs to outputs effectively. In recent times, many researches have been conducted to evaluate the thermo-physical properties of nanofluids [26-29] as listed in Table 1.

TABLE 1. Applications of GMDH-type ANN for predicting the properties of nanofluids

Research	Algorithm	Results	Reference
Prediction of viscosity of nine nanofluids	GMDN-type ANN	• Predicted viscosity values high accuracy with 2.14% average absolute relative deviation with0.9978 regression factor.	[26]
Estimation of volume fraction concentration on dimensional parameters	GMDN-type ANN	• Nusselt number showed direct relation with volume fraction while inverse relation was noticed for Reynolds number and magnetic parameter.	[27]
Predicting the effects of processing parameters on viscosity of Al_2O_3/DW nanofluid	GMDN-type ANN	• Viscosity showed direct relation with volume fraction (0-5%) and inverse relation with temperature (20-70°C).	[28]
Modelling the pressure drop and convective heat transfer coefficient for Al_2O_3/DW nanofluid in flat tubes	GMDN-type ANN	• Effective precision was noticed in predicted results.	[29]

2.2 Multilayer perceptron neural network (MLNN): MLP neural networks have found prominent application in nanofluids research compared to other types of artificial neural networks (ANNs). These networks consist of interconnected neurons organized in layers with unidirectional connections to subsequent layers. A significant attribute of MLP neural networks, particularly when employing the Backpropagation (BP) training approach, lies in their capacity to establish nonlinear mappings from input data to outputs based on acquired rules from the provided data. The training process of these ANNs involves iteratively updating biases and weights using the backpropagation method [11]. MLNN, due to their capacity to process input and output data for tasks like classification and regression, have garnered extensive utilization across diverse domains, including pattern recognition, image and speech processing, natural language processing, and financial modelling, among others. However, their effectiveness heavily relies on an abundant supply of labelled training data to prevent overfitting and ensure robust generalization. Despite their versatility, MLNNs can be computationally demanding and necessitate significant computational resources for training and inference, particularly when handling large-scale and high-dimensional datasets. In contemporary studies, numerous investigations have been undertaken to assess the thermophysical characteristics of nanofluids using MLNN [30-33], which are detailed in Table 2.

TABLE 2. Applications of ML Pneural network for predicting the properties of nanofluids

Research	Algorithm	Results	Reference
Modelling the thermal conductivity of graphene nanofluid	MLP neural network	• Great accuracy with the obtained results in the temperature range of 20-50°C	[30]
Predicting the viscosity of nanofluids with varying concentration, temperature and nanoparticles size	MLP neural network	• Precise estimation of viscosity of eight types of nanofluids	[31]
Measuring the viscosity of TiO_2/DW nanofluid	MLP neural network	• Results showed that at higher nanoparticles concentration, it's difficult to predict the corelations	[32]
Estimation of viscosity of propylene glycol and water mixture based CuO nanofluid	MLP neuro network	• Result of ANN were in good accuracy with the experimental results	[33]

The thermohydraulic properties of an Al_2O_3/DW nanofluid were investigated in channels with discrete heat sources, using numerical solutions that incorporated temperature-dependent properties (Figure 2) [34]. The study revealed periodic variations in thermal conductivity along the channels, with an increase in amplitude observed as the nanoparticle concentration was augmented and the particle diameter was reduced. To predict the convective heat transfer coefficient and pressure loss, a Multi-Layer Perceptron (MLP) neural network was employed. The developed model exhibited remarkable performance, achieving average relative errors of 0.0029% for pressure loss and 0.0071% for convective heat transfer coefficient prediction.

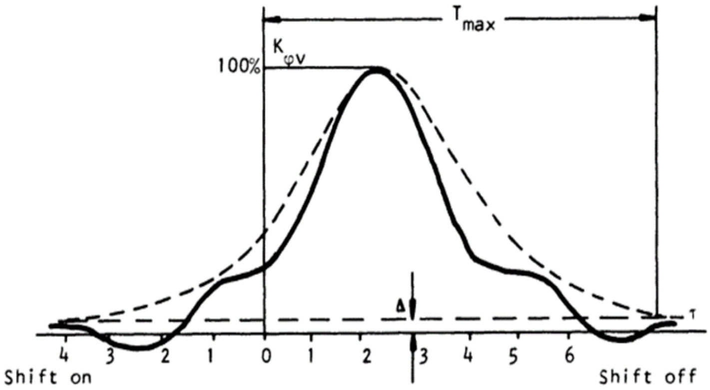

FIGURE 2. Time interval profile

A MLP neural network was employed to model heat transfer in laminar free convection of water-copper nanofluid within a differentially heated square cavity as shown in figure 3 [35]. The nanofluid was treated as a non-Newtonian liquid. The neural network was trained using the resilient-propagation approach, with input and output patterns obtained from concurrent numerical solutions. The neural network demonstrated accurate prediction of heat transfer within the specified domain, aligning with the training data.

2.3 Generalized regression neural network (GRNN): GRNN is a type of artificial neural network (ANN) that has demonstrated efficient training, simplicity, and versatility in function approximation and prediction. Several research papers in the literature have utilized GRNN for the evaluation of nanofluids. The performance and pollutant emissions of a compression ignition engine using diesel nanoparticles fuel were assessed. The Al_2O_3 nanoparticles were employed as additives in the diesel fuel. The results demonstrated a significant impact on engine efficiency, leading to reduced specific fuel consumption compared to conventional methods using base fuels [36]. To establish a correlation between fuel consumption, brake power, CO, HC, and NOx, a GRNN neural network was constructed. Various speeds and alumina nanoparticles were utilized as input data for the model. The predicted results of the model exhibited mean square errors of 8.6470e-4, 9.6346e-5, 0.0213, 2.5836e-4, and 0.0088 for fuel consumption, power, HC, NOx, and CO, respectively. Some researchers compared the predicted data with experimental results [37], while others referenced existing literature [38]. It is important to acknowledge that, given the intricacy of the issues and diverse influencing factors, these correlations often offer models specific to certain types of nanofluids.

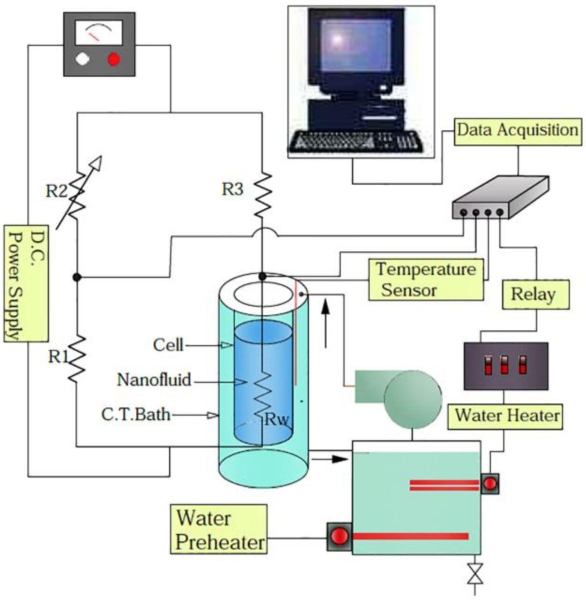

FIGURE 3. Set up designed to estimate thermal conductivity

2.4 Radial basis function artificial neural network (RBF-ANN): RBF neural networks are classified as two-layer architectures due to their training procedure, which comprises two distinct steps or layers. In the initial step, the input data set is exclusively utilized to determine the variables of the basic functions, i.e., the first-layer weights. The subsequent step is supervised in nature, as it necessitates both input data and corresponding target data. It is noteworthy that optimization is accomplished using the conventional least squares method. In current research, extensive investigations have been conducted to analyse the thermophysical properties of nanofluids employing RBF-ANN [39-40], as documented in Table 3.

TABLE 3. Applications of RBF-ANN for predicting the properties of nanofluids

Research	Algorithm	Results	Reference
Modelling the viscosity of nanofluid	RBF-ANN	• Great accuracy with the obtained viscosity value, which showed direct relation with increasing temperature	[39]
Predicting the characteristics of 3 nanofluids with surfactant on pool boiling of water on horizontal rod heater	RBF-ANN	• The findings demonstrate that the treated water exhibited higher boiling efficiency than distilled water. • The incorporation of alumina, SDS, and the surfactant-zinc oxide combination improved boiling performance, while the addition of nano-silica reduced the pool boiling factor. • Moreover, the model outputs aligned consistently with the experimental results.	[40]

3. CONCLUSION

The utilization of Artificial Neural Networks (ANN) is favoured due to their precision and ease of formulation without requiring complete knowledge of the system. These AI algorithms are simple to apply, adapt, and can overcome lengthy time delays. Among various neural network models, the Multilayer Perceptron (MLP) neural network has been extensively studied and employed in the field of nanofluids due to its simplicity. In nanofluid research, the most commonly used neural network model is MLP, while the Radial Basis Function Neural Network (RBF-ANN) is the preferred training method. Although MLP is widely employed, RBF neural networks have also found significant application in the nanofluids domain. Despite requiring more neurons than standard feed-forward ANNs, RBF-ANN can be developed in a shorter time compared to MLP neural networks. Furthermore, the Generalized Regression Neural Networks (GRNNs) exhibit a simple structure that reduces learning time, making them particularly suitable for nanofluids modelling when ample training vectors are available. Consequently, for nanofluids with a large number of samples, the use of RBF-ANN is recommended. However, it is important to acknowledge that despite the efficiency of neural networks in predicting nanofluid characteristics, selecting the appropriate ANN type and determining its configuration still pose challenges. Further research and exploration are needed in this area.

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