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Modeling and prediction of viscosity of water-based nanofluids by radial basis function neural networks

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ABSTRACT

Due to the fact that the viscosity of nanofluids can be affected by many factors, it is difficult to establish an accurate prediction model using traditional model-driven methods. To address this problem, a new viscosity prediction approach based on radial basis function (RBF) neural networks is proposed in this paper. Two RBF neural networks are proposed, one with 5 input variables, the other with 4 input variables. Both models take into account the effects of nanoparticle volume concentration, nanoparticle diameter, nanoparticle density and the viscosity of base fluid, while the 5-input model also considers the effect of temperature. Two different types of nanofluids, namely Al_2O_3–water and CuO–water, are used to evaluate the effectiveness of the proposed models. The comparisons demonstrate that the predicted viscosity of RBF neural networks agree well with the experimental data, which outperforms many existing theoretical and empirical models. The results also show that the prediction performance of RBF neural networks can be further improved when the temperature is added as an input variable.

1. Introduction

With the ever-increasing demands in performance and compactness of heat exchange devices, different heat transfer technologies have been developed by increasing the heat transfer area or using efficiently heat transfer structure [1]. However, the performances of these enhancement approaches depend much on manufacturing technologies. Heat transfer fluid is another key factor that affects the heat transfer performance. Conventional heat transfer fluids (such as water, ethylene glycol and oil) have relative poor thermal conductivity in comparison with metal or metal oxide [2]. Considered as the new generation of heat transfer fluid, nanofluids [3] is a kind of special solid–liquid suspensions consisting of the conventional heat transfer fluid and different nanometer-sized particles (such as copper (Cu), copper oxide (CuO), aluminum oxide (Al_2O_3), titanium dioxide (TiO_2), silica (SiO_2), gold (Au), silver (Ag), or carbon nanotube). Over the past decade, many investigations have found that nanofluids had superior heat transfer performances [4–11]. For example, Xuan and Li [4] presented an experimental investigation on the convective heat transfer and flow feature of Cu–water nanofluids. Their results indicated that the suspended nanoparticles could enhance the heat transfer performance of base fluid, and more than 39% heat transfer enhancement was obtained at 2% nanoparticle volume concentration. Yu et al. [5] reported that the heat transfer performance of base fluid could be increased about 15%–40% by using nanofluids as heat transfer fluid. With the superior characteristics of nanofluids, some researchers attempted to enforce the heat transfer process with nanofluids, which brings a new chance to enhance the heat transfer [12].

The thermophysical parameters are the basic parameters of nanofluids that can reflect the flow and heat transfer performance of fluids. Nowadays, the specific heat and density of nanofluids can be calculated accurately according to the principle of energy conservation and mass conservation [13]. However, existing studies have difficulty in explaining the thermal conductivity and viscosity enhancement mechanism of nanofluids, which may slow down the further development of nanofluids. As a very important thermophysical parameter, viscosity can describe the internal resistance of nanofluids to flow [14]. In industrial applications, both the pumping power and convective heat transfer coefficient are influenced by viscosity [15]. Therefore, it is very necessary to study the viscosity of nanofluids for future understanding of the rheological behavior and stability of nanofluids [16].

In recent years, many experimental and theoretical investigations have been conducted to study the viscosity of nanofluids. Mahbubul et al. [14] and Sundar et al. [16] reviewed the latest developments on the viscosity of nanofluids from different analyses of experiment and theory. Through their studies, it was found that the viscosity of nanofluids could be enhanced in comparison with that of base fluid and affected by nanoparticle volume concentration, temperature, nanoparticle size, nanoparticle properties and base fluid. However, the specific influence mechanism of each factor is still not very clear and there are also some inconsistencies in existing literatures. For example,

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the results obtained by Prasher et al. [17], Garg et al. [18], Rea et al. [19], Maïga et al. [20] and Godson et al. [21] showed that the viscosity of nanofluids could increase linearly with the increase of nanoparticle volume concentration, while some investigations [22–24] observed a nonlinear trend. In addition, many researchers reported the viscosity of nanofluids decreased non-linearly with the increase of temperature [15,25,26]. However, others showed that the relative viscosity of nanofluids was independent of temperature [17,22,27]. Furthermore, some studies [17] showed that the size of nanoparticle did not have a significant impact on the viscosity of nanofluids. However, many researchers [25,28,29] found that nanoparticle size was very important to determine the viscosity of nanofluids and viscosity could increase with the decrease of nanoparticle size.

To effectively predict the viscosity of nanofluids, many theoretical models and empirical correlations have been suggested in the literatures. Based on the assumption of a linearly viscous fluid containing suspensions of spherical particles, Einstein's model [30] can be effectively used to predict the viscosity of nanofluids at very low nanoparticle volume concentration ($\leq$0.02%). Considering the effect of the addition of one solute-molecule, Brinkman [31] extended the Einstein's viscosity model to a moderate nanoparticle volume concentration (up to 4%) in 1952. Graham [32] proposed the viscosity model for nanofluids with the effects of nanoparticle size and interparticle spacing. Besides, taking into account the effect of liquid layer, Yu and Choi [33] developed a new model to express the viscosity of nanofluids. However, there is no appropriate theory to obtain the thickness of liquid layer so far. In order to improve the prediction accuracy of the theoretical models, the effects of Brownian motion on the viscosity of nanofluids were studied by Batchelor et al. [34] and Masoumi et al. [35]. In addition, Lundgren et al. [36] and Frankel et al. [37] also developed theoretical models to calculate the viscosity of nanofluids based on the Einstein's model. Due to the effects of various uncertain factors, most of theoretical models are only suitable for predicting the viscosity of nanofluids at very low nanoparticle volume concentration and cannot describe the viscosity of nanofluids exactly in a wide range of nanoparticle volume concentration. In order to solve this problem, different empirical correlations were developed based on a large number of experimental data. For example, Tseng and Lin [38] presented an exponential correlation for TiO_2–water nanofluids considering the effect of nanoparticle volume concentration on viscosity. The viscosity of two water-based nanofluids consisting Al_2O_3 (36 nm, 47 nm) and CuO (29 nm) nanoparticles were measured by Nguyen et al. [39,40] and then they proposed the empirical correlations considering the effects of nanoparticle volume concentration and temperature. Besides, many other correlations also were developed to represent the effect of temperature on the viscosity of nanofluids. For instance, a correlation between temperature and viscosity for pure fluids was proposed by White [41] in 1991. Furthermore, Abu-Nada et al. [42] and Masoud Hosseini et al. [43] respectively developed different viscosity correlations based on the experimental data of Nguyen et al. [39,40] for Al_2O_3–water nanofluids by taking into account the effects of both nanoparticle volume concentration and temperature. Although the effects of some factors such as temperature, nanoparticle volume concentration, nanoparticle size, the Brownian motion and aggregation of nanoparticles have been discussed, the investigations indicated that there were still no commonly accepted theoretical model and empirical correlation for the prediction of viscosity of all nanofluids with respect to temperature, base fluid, nanoparticle type, volume concentration and size. Hence, there is a need to find an alternative approach that is able to provide a quick and accurate solution to viscosity prediction of nanofluids.

Artificial neural networks (ANNs) is one of the data-driven modeling approaches, which has a strong nonlinear mapping ability and can approximate any nonlinear model theoretically [44]. As a black box model, ANN can approximate the relationships among input and output variables involved in a physical process. Nowadays, ANN has become increasingly popular for predicting the thermophysical properties (mainly thermal conductivity) [45–53] and thermal behavior [54] of nanofluids due to its high speed, simplicity and large capacity.

In this paper, a novel viscosity prediction approach based on RBF neural networks is proposed as an alternative to the model-based approach to provide quick and accurate viscosity prediction of nanofluids. Considering the advantages of RBF neural networks, the modeling method based on RBF neural networks is introduced firstly. Then, according to the available experimental measurements from literatures, two different RBF neural networks (a 5-input model and a 4-input model) are proposed for predicting the viscosity of two most common nanofluids, which are Al_2O_3, CuO and with water as base fluid. Finally, the obtained prediction results by RBF neural networks are compared with the experimental data and many existing theoretical models to evaluate the prediction performance of the proposed method.

2. Modeling method based on RBF neural networks

As a kind of feed-forward networks, RBF neural networks were firstly introduced into the literature by Broomhead and Lowe in 1988 [55]. Compared with BP neural networks which are based on a stochastic approximation method, RBF neural networks can be regarded as a curve-fitting problem in a high dimensionality space. It can approximate arbitrary continuous function with arbitrary precision [56].

RBF neural networks generally have a three-layer feed forward architecture with an input layer, a hidden layer and an output layer, which is illustrated in Fig. 1. The input layer, consisting of n input nodes, is responsible for propagating the input vector to the hidden layer. The hidden layer is used to transform the input from the input space to the hidden space which is of higher dimensionality than the input layer [57]. Different from other neural networks, each node in the hidden layer of RBF neural networks is centered at a particular point with a given radius and calculates the distance between the input vector and its own center [58]. Then, the calculated distance is transformed using the basis function. The output from each node in the hidden layer is multiplied by its connection weight and then fed into the output layer. Finally, the output layer gives the final responses by linearly summing up all the outputs of the hidden layer.

Essentially, the RBF neural networks is a mapping in Euclidean space: $T : X^n \rightarrow Y^q$. The output of the output layer can be formed by a linear combination of the hidden layer responses, which is defined as follows [59].

$$y_k = \sum_{i=1}^{m} \omega_{ik} R_i(X), \quad (k = 1, 2, \cdots, q) \tag{1}$$

where X is the input vector, $y_k \in Y^q$ is the output of kth output layer node, $R_i(X)$ is the response of ith hidden layer node, ω_{ik} is the connection weight between the ith hidden layer node and the kth output layer node, m is the number of the hidden layer nodes and q is the number of the output layer nodes.

The response of the hidden layer node is determined by the radial basis functions. Gauss function [59] is selected as the activation function in this paper.

$$R_i(X) = \exp\left(-\frac{\|X - c_i\|^2}{2\sigma_i^2}\right), \quad (i = 1, 2, \cdots, m) \tag{2}$$

where $\|\|$ is the Euclidean distance, c_i and σ_i are the center and width of the ith RBF, respectively.

From Eq. (2), it is clear that $R_i(X)$ can obtain the maximum value when $X = c_i$. And $R_i(X)$ decreases with the increase of $\|X - c_i\|$. Therefore, only the input vector X that is near the center of the radial basis function can activate the nodes of the hidden layer.

An unsupervised learning stage is often used for adjusting the parameters of the hidden layer including RBF center c_i and width σ_i,