Modeling of thermal conductivity of ZnO-EG using experimental data and ANN methods ☆

Mohammad Hemmat Esfe [a,*], Seyfolah Saedodin [b], Ali Naderi [b], Ali Alirezaie [b], Arash Karimipour [a], Somchai Wongwises [c,*], Marjan Goodarzi [d], Mahidzal bin Dahari [e]

[a] Department of Mechanical Engineering, Najafabad Branch, Islamic Azad University, Isfahan, Iran
[b] Faculty of Mechanical Engineering, Semnan University, Semnan, Iran
[c] Fluid Mechanics, Thermal Engineering and Multiphase Flow Research Lab. (FUTURE), Department of Mechanical Engineering, Faculty of Engineering, King Mongkut's University of Technology Thonburi, Bangmod, Bangkok 10140, Thailand
[d] Young Researchers and Elite Club, Mashhad Branch, Islamic Azad University, Mashhad, Iran
[e] Department of Mechanical Engineering, Faculty of Engineering, University of Malaya, 50603, Kuala Lumpur, Malaysia

ARTICLE INFO

Available online 7 February 2015

Keywords:
Thermal conductivity
MgO-EG
Artificial neural network
Nanofluid

ABSTRACT

In the present study, the thermal conductivity of the ZnO-EG nanofluid has been investigated experimentally. For this purpose, zinc oxide nanoparticles with nominal diameters of 18 nm have been dispersed in ethylene glychol at different volume fractions (0.000625, 0.00125, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, and 0.05) and temperatures (24–50 °C). The two-step method is used to disperse nanoparticles in the base fluid. Based on the experimental data, an experimental model has been proposed as a function of solid concentration and temperature. Then, the feedforward multilayer perceptron neural network has been employed for modeling thermal conductivity of ZnO-EG nanofluid. Out of 40 measured data obtained from experiments, 28 data were selected for network training, while the remaining 12 data were used for network testing and validating. The results indicate that both model and ANN outputs are in good agreement with the experimental data.

1. Introduction

It was 20 years ago when, for the first time, nanoparticles were used in common fluids as additives to increase their heat transferring [1]. Since then, a wide range of studies have been done in this area and different nanoparticles have been used in heat-transferring fluids. Therefore, a collection of data has been obtained to produce the fluids commercially and to use them in the industrial systems. However, after spending so much money and doing a lot of research in this area, some scholars have claimed that studies done on nanoparticles do not have a necessary cohesion, and the obtained results are very different from each other in some cases.

Most of the research done in this area has focused on thermal conductivity in the calculation of nanofluids because the scholars believe that when thermal conductivity of nanofluids increases, their heat transferring increases too [2–5].

However, the studies have not stopped here, and some scholars have investigated other features of these fluids. The viscosity of nanofluids is the second important issue from the scientists' point of view because adding solid particles to the fluid will cause a pressure drop in the system, and the power consumption of the pump will increase. Hemmat Esfe et al. [6] have studied the heat transferring of functionalized COOH DWCNTs-water nanofluids and obtained the friction factor and pressure drop for different Reynolds numbers in the experiment. Fuoc et al. [7] have also studied MWCNT nanofluids, which were suspended by chitosan. They presented their result based on the cut rate and concluded that this nanofluid shows non-Newtonian behavior. A lot of different studies have been conducted about the issue [8–10].

Diameter size of the nanoparticles is one of the other factors that has been noticed in the studies of nanofluids. The investigations [11–14] indicate that the smaller the diameter of the nanoparticles, the larger the thermal conductivity. Nasiri et al. [15] reported that in carbon nanotubes, when the diameter size of nanotubes is smaller, the nanofluid shows greater thermal conductivity.

Additionally, the effect of temperature on the thermal conductivity of nanofluids has been studied in some studies [16–20], and most of them proved that there is a direct relationship between thermal conductivity fraction and temperature.

The volume fraction of the solid particles is also another feature that has been investigated by the researchers [21–23]. Thermal conductivity of nanofluids increases in a non-linear way by an increase in solid volume fraction.

Simultaneously, in experimental studies, analytical and numerical studies have been done on nanofluids, as well [24–26]. Different models

☆ Communicated by W.J. Minkowycz.

* Corresponding authors.
E-mail addresses: M.hemmatesfe@semnan.ac.ir (M. Hemmat Esfe), somchai.won@kmutt.ac.th (S. Wongwises).

http://dx.doi.org/10.1016/j.icheatmasstransfer.2015.01.001
0735-1933/

have, thus far, been proposed for predicting thermal conductivity and viscosity of nanofluids. The other method of predicting nanofluids behaviors involves using an artificial neural network for conductivity fraction and viscosity of nanofluids. Hojjat et al. [27] conducted an experimental study on thermal conductivity of three different nanofluids, alumina, titania, and CuO. Then, they modeled the experimental data using the neural network. They used three factors—temperature, volume fraction of nanoparticles, and thermal conductivity of nanoparticles. In another study, Hemmat Esfe et al. [28] measured the thermal conductivity of magnesium oxide-ethylene glycol nanofluids and modeled experimental data by an artificial neural network. Their variables in this experiment were temperature, volume fraction, and the diameter of the nanoparticles. They attained a model that is very accurate.

2. Experimental

2.1. Nanofluid preparation

Measuring thermal conductivity, ZnO-EG nanofluid was provided by two-step methods. Furthermore, the XRD pattern and a transmission of a microscope electron image of the particles, which take from the company, are displayed in Fig. 1.

First, the ZnO nanoparticles required for the desired volume concentrations (i.e., 0.05 (5.0%), 0.04 (4.0%), 0.03 (3.0%), 0.02 (2.0%), 0.015 (1.5%), 0.01 (1.0%), 0.005 (0.5%), 0.0025 (0.25%), 0.00125(0.125%), and 0.000625 (0.0625%)) were weighed and then added with the base fluid.

After mixing the ZnO nanoparticles with ethylene glychol, the samples were subjected to an ultrasonic vibrator(400 W, 20 KHz) for about 3–5 h.

2.2. Thermal conductivity of the nanofluid

Thermal conductivity of the ZnO-EG nanofluid has been investigated experimentally. The ZnO-EG nanofluid with particle diameters of 18 nm has been examined by the KD2 pro instrument at different volume fractions up to 5% over the temperature ranging from 24 to 50 °C. Fig. 2 shows the thermal conductivity ratio with respect to a solid volume fraction at different temperatures.

2.2.1. Proposed new correlation

In this study, experimental data have been employed as a correlation pattern for the experimental results. The thermal conductivity of the ZnO-EG nanofluid has been studied by developing a non-linear regression equation that includes the effect of the volume fraction and the fluid temperature. Measuring thermal conductivity of the ZnO-EG nanofluid with average particle diameters of 18 nm has been performed in different volume fractions and temperatures.

The desired relationship in this study is $\frac{K_{nf}}{K_b} = f(T, \varphi)$, which fits the thermal conductivity ratio in terms of temperature and volume fraction. Accordingly, multiple relations were derived. Finally, the best model was selected in terms of accuracy. In order to select the best curve-fitting equation, various criteria can be employed. In this study, the mean squared error (MSE) and the mean absolute error (MAE) were used as the main criteria for investigating the correlated model performance, which is calculated by the following relations:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(\left.\frac{K_{\mathrm{nf}}}{K_{\mathrm{b}}}\right|_{\mathrm{Exp}} - \left.\frac{K_{\mathrm{nf}}}{K_{\mathrm{b}}}\right|_{\mathrm{pred}}\right)^2 \tag{1}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|\left.\frac{K_{\mathrm{nf}}}{K_{\mathrm{b}}}\right|_{\mathrm{Exp}} - \left.\frac{K_{\mathrm{nf}}}{K_{\mathrm{b}}}\right|_{\mathrm{pred}}\right| \tag{2}$$

where N is the number of experimental data used in the correlation, $\left.\frac{K_{nf}}{K_b}\right|_{\mathrm{Exp}}$ and $\left.\frac{K_{nf}}{K_b}\right|_{\mathrm{pred}}$ are thermal conductivity of the experimental results and thermal conductivity of the correlated model results, respectively, whose difference shows the curve-fitting error between the real and predicted values.

In order to select the best curve-fitting equation, the MSE and MAE performance criteria were investigated for multiple curve-fitting equations developed for predicting thermal conductivity in terms of temperature and volume fraction from regression equations. Finally, Eq. (3) was selected as the best correlation equation, which is, indeed, the best equation for the results of the regression analysis of the thermal conductivity data at different temperatures and volume fractions compared to other equations.

$$\begin{aligned}\frac{K_{\mathrm{nf}}}{K_{\mathrm{b}}} &= 1.00475 + 2.26216 \times \varphi + 1.57146 \times T \times \varphi^2 + 481.646 \times \varphi^2 \\ &\quad \times \exp(-66.7522 \times \varphi) - 0.0100301 \times T \times \varphi \times \cos(1560.99\varphi)\end{aligned} \tag{3}$$

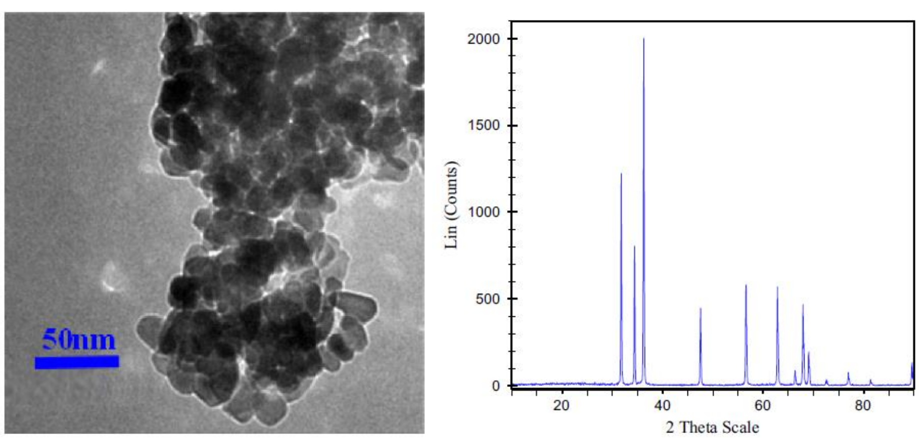

Fig. 1. TEM image and XRD patterns of ZnO nanoparticles.

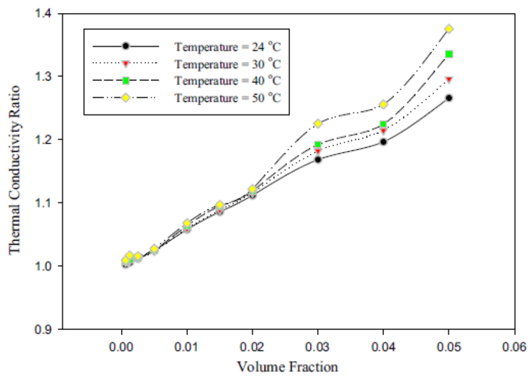

Fig. 2. Thermal conductivity ratio via volume fraction in different temperature.

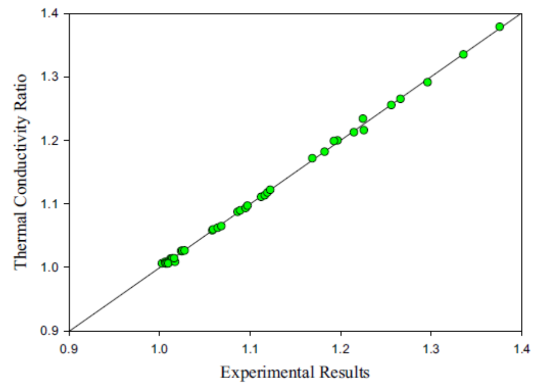

Fig. 3. Correlation regression diagram.

where T and φ represent temperature and volume fraction of the nanofluid, respectively.

Performance criteria for Eq. (3) have been presented in Table 1.

Fig. 3 compares the present experimental model prediction with experimental data for thermal conductivity of the ZnO-EG nanofluid at different temperatures and volume fractions. It can be observed that the thermal conductivity ratio obtained from the correlated model is in good agreement with the thermal conductivity ratio measured for all studied temperatures and volume fractions.

Fig. 4 compares the experimental results with those obtained by the correlated experimental model. As it can be seen, the correlated model properly predicts the thermal conductivity ratio of the nanofluid. It is determined that the maximum error is about 0.0098 at a volume fraction of 4% and in temperature of 40 °C.

According to the experimental results, a correlation was developed to estimate the thermal conductivity ratio using a regression equation. A comparison of the results from the experimental data with those of the correlation model shows that there is good agreement between them, indicating the accuracy of the relation provided in this study.

3. Artificial neural network modeling

Artificial neural network modeling is a non-linear statistical technique that can be used for solving problems that are not solved using conventional statistical methods. Neural networks can be used for modeling complex relations between outputs and inputs or finding patterns between data. Important benefits of ANN compared to other specialized systems include high speed, simplicity, the capability of modeling multivariate problems for solving complex relations between variables, and the ability to derive non-linear relations through training data.

The proper selection of input parameters plays an important role in the ANN method and can improve the predicting quality. This selection is usually based on the physical background of the problem. In order to predict the thermal conductivity ratio for every type of nanofluid, temperature and volume fraction variables are considered as inputs to the neural network. Fig. 5 depicts the network training process.

In this study, the feedforward multilayer percepetron neural network has been used for modeling the thermal conductivity ratio of the ZnO-EG nanofluid. This network has a good ability in estimating non-linear relations and is one of the most common neural network models used in engineering applications.

The multilayer perceptron neural network consists of multiple layers, each of which has a number of neurons. Each neuron in each layer is connected to the neurons in the next layer by weight coefficients. An activation function is determined for the neurons in each layer, which is used for calculating the sum of the input weights and the biases of each neuron in order to produce the output neuron. Developing an ANN involves three steps. The first step is developing the data required for network training. The second step is evaluating different neural network structures in order to select the optimal one. Finally, the third step is testing the neural network using data not previously used in network training. Biased neurons are linked to other neurons in the next layers to develop a constant bias. The most exact and accurate prediction of neural networks is made using the tan-sigmoid function for the hidden-layer neurons and the purelin function for the output-layer neurons. Therefore, the

Table 1
Performance of the correlated model.

Mean square error	$1.0829906{*}10^{-5}$
Mean absolute error	0.0022070592
Maximum error	0.0098439036
Correlation coefficient	0.99949742

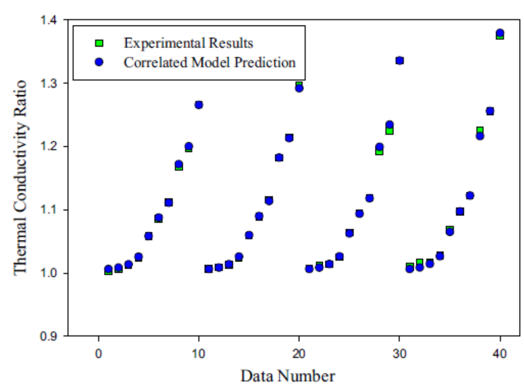

Fig. 4. Comparison between experimental results with those obtained by correlated experimental model.

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