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Thermal conductivity of Cu/TiO_2–water/EG hybrid nanofluid: Experimental data and modeling using artificial neural network and correlation☆

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ABSTRACT

In the present paper, the thermal conductivity of hybrid nanofluids is experimentally investigated. The studied nanofluid was produced using a two-step method by dispersing Cu and TiO_2 nanoparticles with average diameter of 70 and 40 nm in a binary mixture of water/EG (60:40). The properties of this nanofluid were measured in various solid concentrations (0.1, 0.2, 0.4, 0.8, 1, 1.5, and 2%) and temperatures ranging from 30 to 60 °C. Next, two new correlations for predicting the thermal conductivity of studied hybrid nanofluids, in terms of solid concentration and temperature, are proposed that use an artificial neural network (ANN) and are based on experimental data. The results indicate that these two new models have great ability to predict thermal conductivity and show excellent agreement with the experimental results.

1. Introduction

In recent decades, artificial neural networks (ANNs) have significantly grabbed the attention of researchers in different scientific fields. ANNs are a new method for predicting the non-linear behavior of thermal conductivity ratios. The paramount benefits of these networks, compared with prior common methods, are their high speed and ability to solve complicated equations [1].

The thermal conductivity of nanofluids is undoubtedly an important feature that should be measured. Thus, many researchers have conducted different studies on the thermal conductivity of nanofluids [2–9].

In recent years, many researchers have used ANNs to simulate and predict the thermal conductivity ratios of nanofluids in various thermophysical conditions. Kurt and Kayfeci [10] developed an ANN to predict the thermal conductivity ratio of water/EG based on experimental data. Hojjat et al. [11] conducted an investigation using an ANN in order to propose a thermal conductivity model as a function of temperature, solid concentration, and the thermal conductivity of the nanoparticles. In another study, Papari et al. [12] used an ANN to predict the thermal conductivity of nanofluid containing multi-wall carbon nano-tubes (MWCNT) in oil, water, and EG.

Hemmat et al. [13] conducted an experimental investigation on the thermal conductivity of MgO/EG. They proposed a thermal conductivity enhancement model in terms of temperature, solid concentration, and particle size using an ANN, based on the experimental data. Furthermore, in another investigation and based on the experimental data, they proposed two correlations that show the relationships between viscosity, solid concentration, and the nanofluid's temperature [14]. Longo et al. [15] used three-input and four-input artificial neural networks to predict the thermal conductivity ratio of oxide-water nanofluid. They employed the temperature, solid concentration, and thermal conductivity ratio of the nanofluid as the three inputs for both of the networks, with the effect of the nanoparticle clusters' average size also employed for the four-input network. Bhoopal et al. [16] investigated the applicability of ANNs for predicting the thermal conductivity of highly porous metal foams. Modeling of thermal conductivity of ZnO–EG using experimental data and ANN method has been carried out by Hemmat Esfe et al. [17].

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2. Experimental apparatus and procedure

2.1. Nanofluid preparation

Cu/TiO_2–water/EG hybrid nanofluid was produced as the experimental sample using a two-step method and without adding any surfactant. First, using a mechanical mixture, the nanoparticles were dispersed into seven solid concentrations (0.1, 0.2, 0.4, 0.8, 1, 1.5, and 2%); certain amounts of Cu and TiO2 were added into the base fluid for each solid concentration. Next, in order to produce a stable nanofluid, the Cu and TiO_2 nanoparticles were mixed using a magnetic stirrer for 3 h. In the next stage, the produced suspension was inserted into an ultrasonic processor (20 KHz, 400 W, Topsonic, Iran) for 6 h. The ultrasonic processor was used to ensure superb dispersion and break down the agglomeration of the nanoparticles, thus preventing the problem of sedimentation and making a stable suspension. In this way, a long-time stable sample was produced (lasting at least a week) and no sedimentation could be noticed by the naked eye.

2.2. Thermal Conductivity Measurement

The KD2 Pro thermal property analyzer device (Decagon Device, Inc., USA) was used to measure the thermal conductivity of the studied hybrid nanofluid. This instrument uses the hot-wire method. The stainless steel, 60-mm KS-1 sensor with 1.27 mm diameter was used to measure thermal conductivity. In order to measure the thermal conductivity of the prepared sample, the sensor was inserted into the sample vertically to minimize the free convection. Any deviation from the vertical position will bring errors into the reported data. The accuracy of the device is $\pm$ 5%.

The relative thermal conductivity of the Cu/TiO_2–water/EG hybrid nanofluid at different temperatures and solid concentrations is shown in Fig. 1.

2.3. Design and training of an artificial neural network (ANN)

Artificial neural networks are general tools for modeling non-linear functions. They can estimate every non-linear function at a demanded level of accuracy. The flexibility of artificial neural networks to estimate non-linear functions has turned them into invaluable tools for processing data. Moreover, artificial neural networks have a special ability to model complicated correlations. There are three steps in the modeling procedure for artificial neural networks, which are shown in Fig. 2.

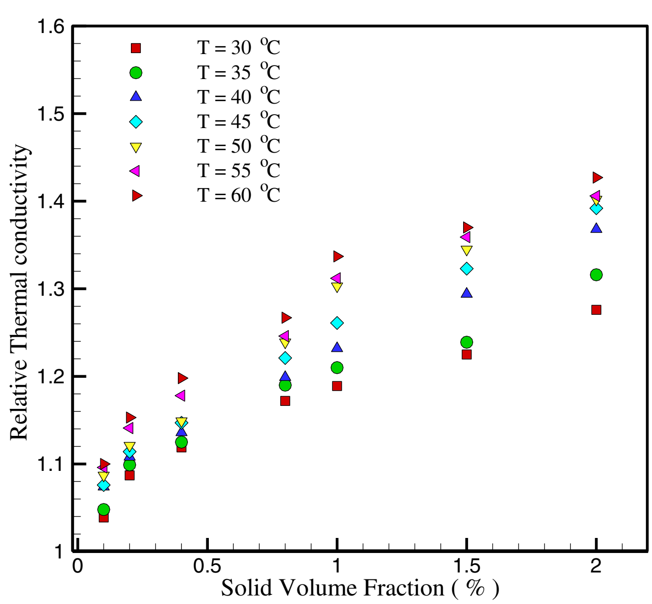

Fig. 1. Relative thermal conductivity of nanofluid versus solid volume fraction at different temperatures.

Selecting adequate input parameters can play an important role in the artificial neural network method and can provide acceptable quality for estimation. In the present study, solid concentration and temperature were used as the input parameters for estimating the thermal conductivity of Cu/TiO_2–water/EG hybrid nanofluid.

A neuron is a basic processing element in modeling artificial neural networks. In a neuron, each input is multiplied by the weight; then, the results are added with each other and with the bias. Then, the network's output is extracted according to Eq. (1).

$$y_k = \phi\left(\sum_{i=1}^{m} w_{kj}x_j + b_k\right) \tag{1}$$

Where x_j is the input, y_k is the output, w_{kj} is the weight, b_k is the bias, and ϕ represents the activation function.

In order to estimate the thermal conductivity, the network must be trained using the experimental data. The core aim of training the network is to achieve an error close to zero through suitable adjustments of educational parameters, such as updating the weights, in order to gain the desired error. In the present study, the Levenberg–Marquardt back-propagation algorithm was used in order to model the thermal conductivity ratio. On these grounds, 70% of the experimental data were used for the training set, while the rest were used for testing and validating the network.

A multi-layer perception (MLP)-feedforward network (Fig. 3) was used to simulate the thermal conductivity ratio with an ANN. This type of network has satisfactory ability to estimate non-linear correlations. Moreover, it is one of the most frequent ANNs in engineering applications.

An activation function is defined for the neurons of each layer, which is employed to determine the sum of the weighted inputs and the bias for generating the neuron output. In this study, the tangent sigmoid function was applied as the activation function in the hidden layer, while the pure linear function was employed as the activation function in the output layer.

The input parameters in different domains may cause a lack of training in the neural network. In order to solve this problem, the input data were normalized to the range from −1 to 1.

The numbers of neurons in the output and input layers were taken into account based on the output and input variables. The number of optimum hidden layers and the neurons of each hidden layer were determined using the trial-and-error method. At first, the structure of the hidden layer of the network starts with few neurons; then, the number of neurons was increased until the training error reached the

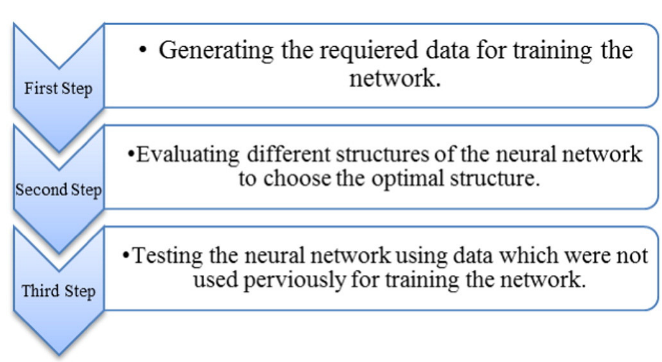

Fig. 2. Steps in modeling an artificial neural network.

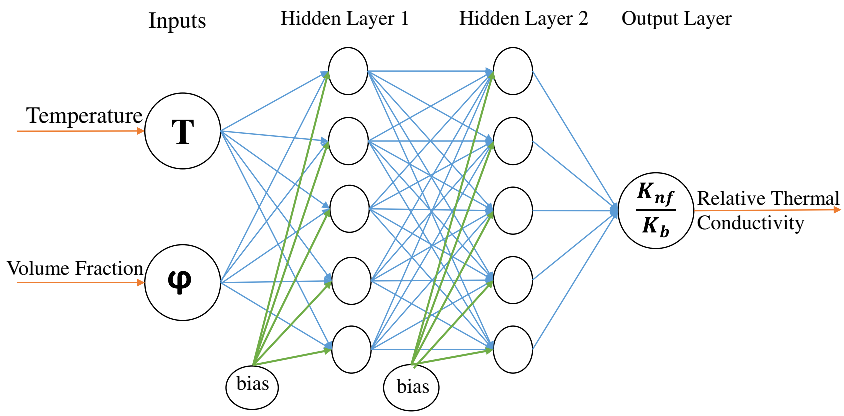

Fig. 3. The multi-layer perceptions (MLP)-feedforward network.

needed condition (mean square error). The mean square error (MSE) was determined using the following correlation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(e_i)^2. \tag{2}$$

Where n is the number of data points and e_i represents the difference between the measured experimental values and the model's estimated values.

3. Results and discussion

3.1. Neural network

In the present study, the thermal conductivity of Cu/TiO_2–water/EG hybrid nanofluid was predicted at different temperatures (30, 35, 40, 45, 50, 55, and 60 °C) and solid concentrations (0.1, 0.2, 0.4, 0.8, 1, 1.5, and 2%) using a multilayer perceptron neural network.

Table 1 shows the trial-and-error method procedures used to find the neural network's optimum structure, in order to predict the thermal conductivity of Cu/TiO_2–water/EG hybrid nanofluid. R_1 represents the correlation coefficient between the output model and the training set, R_2 is the correlation coefficient between the output model and the validation set, R_3 is the correlation coefficient between the output model and the testing set, and R represents the correlation coefficient between the output model and all of the experimental data. The MSE values and correlation coefficients were calculated and compared for the different numbers of neurons. As a result, a multilayer perceptron neural network with two hidden layers and five neurons was considered for each of the hidden layers (Fig. 3). As can be seen in the table, the MSE value in the selected neurons was 2.62E-05. Moreover, the correlation coefficients were very close to 1, with a maximum absolute error of 1.20E-02.

The regression graph of the network after training is shown in Fig. 4. The value of the correlation coefficient was 0.999, which confirms the acceptable performance of the neural network.

The experimental data and results predicted by the ANN are compared and presented in Fig. 5. As can be seen, the experimental data and the model's outputs have good agreement with each other, which highlights the acceptable performance of the neural network used.

3.2. Correlation

In the present study, the experimental data were used as correlation patterns of the experimental results. The curve-fitting model for the thermal conductivity ratio of Cu/TiO_2–water/EG hybrid nanofluid was developed using a non-linear regression equation. This equation is a function of temperature and solid concentration. However, different criteria must be employed to extract the best correlation. For this

Table 1
The procedure of trial and error to find the optimum number of hidden layers and neurons.

Number of hidden layer	Number of neuron in each hidden layers	R_1	R_2	R_3	R	MSE	Maximum absolute error
1	2	0.99327	0.98699	0.9943	0.99242	1.76E-04	0.0343
1	3	0.99559	0.99579	0.99745	0.99559	1.04E-04	2.08E-02
1	4	9.96E-01	9.99E-01	9.97E-01	9.96E-01	9.58E-05	2.57E-02
1	5	9.95E-01	9.92E-01	0.99402	0.99493	1.19E-04	2.38E-02
1	6	9.97E-01	9.96E-01	0.98231	9.95E-01	1.04E-04	2.98E-02
1	7	9.97E-01	9.97E-01	0.99695	9.96E-01	1.02E-04	1.77E-02
1	8	9.97E-01	9.99E-01	9.98E-01	9.97E-01	5.66E-05	1.60E-02
1	9	1.00E + 00	9.97E-01	9.86E-01	9.99E-01	3.35E-05	1.63E-02
1	10	9.99E-01	9.97E-01	9.98E-01	9.99E + 04	3.53E-05	1.61E-02
2	2	9.94E-01	9.99E-01	9.97E-01	9.93E-01	1.56E-04	2.30E-02
2	3	9.96E-01	9.93E-01	9.96E-01	9.95E-01	1.07E-04	2.26E-02
2	4	9.98E-01	1.00E + 00	9.98E-01	9.98E-01	3.74E-05	1.34E-02
2	**5**	**9.99E-01**	**9.98E-01**	**9.99E-01**	**9.99E-01**	**2.62E-05**	**1.20E-02**
2	6	9.98E-01	1.00E + 00	9.64E-01	9.98E-01	5.23E-05	2.99E-02
2	7	9.99E-01	1.00E + 00	9.86E-01	9.97E-01	7.34E-05	5.37E-02
2	8	9.99E-01	9.99E-01	9.97E-01	9.98E-01	3.95E-05	1.27E-02
2	9	9.96E-01	9.98E-01	1.00E + 00	9.97E-01	6.54E-05	1.97E-02
2	10	9.99E-01	9.94E-01	9.97E-01	9.98E-01	5.06E-05	0.0297

Bold data are the number of hidden layer and neuron in each hidden layers which have minimum errors.

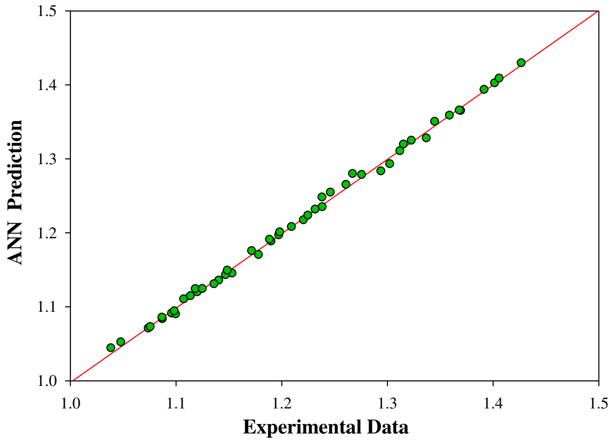

Fig. 4. The regression graph of the network after training.

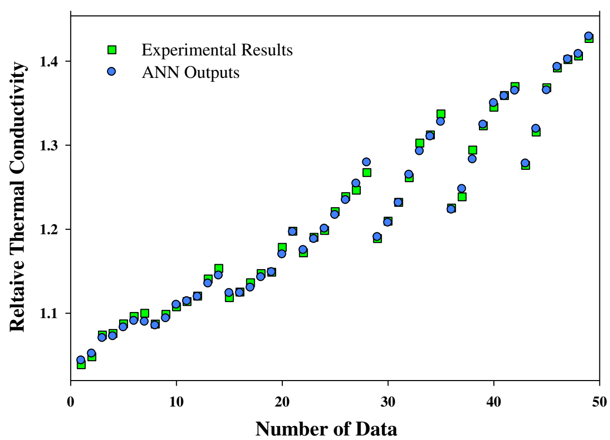

Fig. 5. Comparison between experimental results and ANN outputs.

purpose, the MSE and correlation coefficient were calculated and compared. Finally, the following equation was selected as the equation with the least error:

$$\frac{K_{nf}}{K_b} = 1.07 + 0.000589 \times T + \frac{-0.000184}{T \times \varphi} + 4.44 \times T \times \varphi \times \cos(6.11 + 0.00673T + 4.41 \times T \times \varphi - 0.0414 \sin(T)) - 32.5\varphi. \quad (3)$$

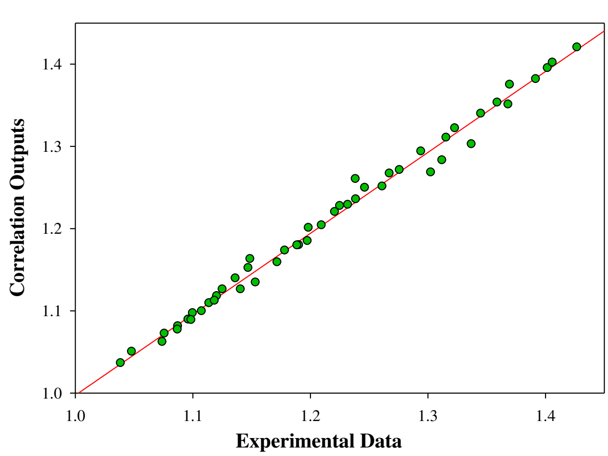

Fig. 6. The regression graph of the correlation model.

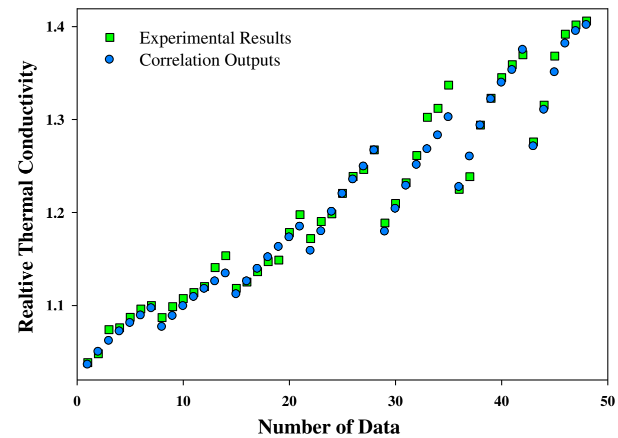

Fig. 7. Comparison between experimental results and correlation.

Where $\frac{K_{nf}}{K_b}$ is the thermal conductivity of Cu/TiO_2–water/EG hybrid nanofluid, T is temperature, and φ represents the solid volume fraction of the nanofluid.

Fig. 6 shows the regression graph of the correlation model. Furthermore, the experimental results were compared with those obtained from the correlation outputs in Fig. 7. This figure shows that the equation can predict the thermal conductivity ratio of the nanofluid precisely. The MSE was $1.3310 * 10^{-4}$, and the maximum error and correlation coefficient were 0.0347 and 0.955, respectively.

3.3. Comparing the correlation models with the experimental results

The relative thermal conductivity of Cu/TiO_2–water/EG hybrid nanofluid obtained from the experiment, correlation model, and ANN model are compared in Fig. 8. There was good agreement between the experimental results and the values predicted by both models. The MSE values for the neural network and correlation models were $2.62 * 10^{-5}$ and $1.3310 * 10^{-6}$, respectively; thus, the ANN approximation was more accurate. Therefore, it is possible to use these models to predict the thermal conductivity ratio of Cu/TiO_2–water/EG hybrid nanofluid with high accuracy.

4. Conclusions

In the present study, the thermal conductivity ratio of Cu/TiO_2–water/EG hybrid nanofluid was investigated using ANN and correlation

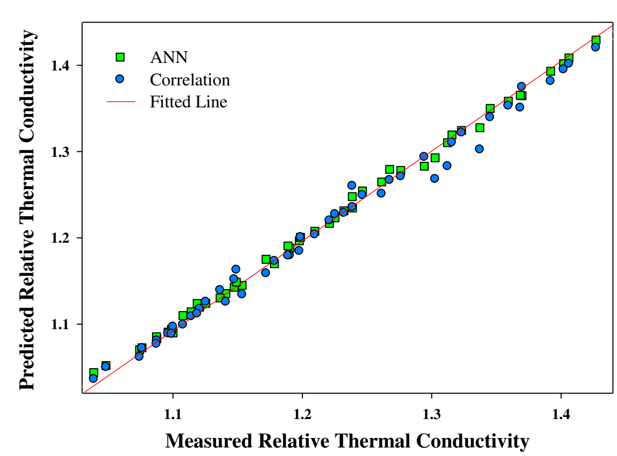

Fig. 8. Obtained results from experiment, correlation and ANN model.

models. For this purpose, experimental data were used involving different temperatures, ranging from 30 to 60 °C, and solid concentrations ranging from 0.1 to 2%. For the artificial neural network, the MSE and correlation coefficient were $2.62 * 10^{-5}$ and 0.999, respectively. Moreover, the MSE of the correlation model was $1.3310 * 10^{-4}$, with a correlation coefficient is 0.995. Both models have acceptable capabilities for predicting thermal conductivity. However, the ANN model showed better performance in predicting the thermal conductivity of the nanofluid.

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