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Applicability of artificial neural network and nonlinear regression to predict thermal conductivity modeling of Al_2O_3–water nanofluids using experimental data☆

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ABSTRACT

In the present study, the thermal conductivity of Al_2O_3–water nanofluid at different temperatures and solid volume fractions has been modeled by artificial neural network (ANN) and correlation using experimental data. The thermal conductivity of the nanofluids at different fluid temperatures, ranging from 26 to 55 °C is employed as training data for ANN. Furthermore, based on the experimental data and using artificial neural network, a correlation for modeling the thermal conductivity of the nanofluid in terms of temperature and solid volume fraction is proposed. The results show that the proposed correlation has good ability for predicting the thermal conductivity of the nanofluids. On the other hand, the ANN model shows excellent agreement with the results of the experimental data.

1. Introduction

The mixture of nanoparticles with a base fluid (water, ethylene glycol, oil, etc.) is called nanofluid. Nanofluids are new type of fluids which have various applications in industrial and engineering apparatus. Thermal conductivity of nanofluids is one of the important features that play a vital role in cooling and heating applications. In this ground, many researchers have conducted various investigations [1–6]. Moghadassi et al. [7] conducted an investigation on the effective thermal conductivity of nanofluid. Based on dimensionless groups, they proposed a new model to predict the effective thermal conductivity of nanofluid. In another study, Barbes et al. [8] experimentally investigated the thermal conductivity and specific heat capacity of Al_2O_3–water and Al_2O_3–ethylene glycol (EG). They conducted the experiments in different solid concentrations and temperatures.

In recent years, artificial neural networks (ANN) grabbed the attention of many researchers in various industrial and engineering fields. High speed processing, extensive capacity, and simplicity are the primary benefits of using ANN compared with the classical methods. Due to these advantages of ANN, many researchers have used this method for predicting the thermophysical features of nanofluids and other engineering applications [9–12]. Bhoopal et al. [13] investigated the application of artificial neural networks for predicting the effective thermal conductivity. They results showed that the outputs of the artificial neural network have a good agreement with the experimental results. Hemmat Esfe and Saedodin [14] presented an experimental investigation on the effects of temperature and particle volume concentration on the dynamic viscosity of ZnO–EG nanofluid. Two experimental correlations were developed based on the data, which relate the viscosity with particle volume fraction and the nanofluid temperature. The proposed models showed reasonably excellent agreement with the experimental results. Hojjat et el. [15] conducted an experimental investigation on the thermal conductivity of three different nanofluids containing Al_2O_3, TiO_2 and CuO nanoparticles. They conducted the experiments in different solid concentrations, up to 0.5 wt%, and temperatures. Furthermore, some new models were proposed using ANN to predict the thermal conductivity in terms of temperatures, solid concentration and the thermal conductivity of the nanoparticles. In another study, Papari et al. [16] employed the neural network to predict the thermal conductivity of nanofluids containing multi-walled carbon nanotubes (MWCNTs). They compared the obtained results with experimental results. In order to predict the thermal conductivity of oxide-water nanofluids, Longo et al. [17] used artificial neural network.

In this study, artificial neural network (ANN) and correlation were used for modeling the thermal conductivity of Al_2O_3/water nanofluid in various temperatures and solid volume fractions. The comparison has been conducted between measured data with ANN and correlation outputs. It was shown that the models are in a good agreement with the experimental results.

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2. Experimental study

2.1. Nanofluid preparation

No-one would disagree that the first and most important step for investigating the nanofluids and their properties is the process of the preparation of them. This is important since some phenomenon such as sedimentation and agglomeration of the nanoparticles in the base fluid must be addressed using special methods in order to create a stable suspension. In this study, using two-step method and by dispersing the Al_2O_3 nanoparticles in DI water, as the working fluid, the nanofluids are prepared at different solid volume fractions (0.25, 0.5, 1, 2, 3, 4, and 5%). The nanoparticles with the average diameter of 5 nm were used, which are purchased form the US Research Nanomaterial, Inc. Table 1 shows the properties of the nanoparticles. It was found in the separate experimental TEM image of the particles that the particles are approximately spherical in shape.

After the nanoparticles are weighted carefully for each solid volume fraction, they are added into the water gradually. Next, using a mechanical stirrer, the mixture is stirred for about 45 min. After that, the suspension is put inside an ultrasonic vibrator (Topsonic, Iran) for 3 h to break down the agglomeration of the nanoparticles. Using the stirrer and ultrasonic vibrator, the sample is prepared in the way no sedimentation and agglomeration is observed with the naked eyes for a long period of time (at least one week).

2.2. Thermal conductivity measurement

Using a KD2 Pro instrument, manufactured by Decagon Device Inc., the thermal conductivity of Al_2O_3–water nanofluid in various solid volume fractions and temperatures (ranging from 26 to 55 °C) is measured. The KD2 Pro instrument was based on the transient hot wire method. The accuracy of the instrument is $\pm 5\%$. To make sure of the experimental accuracy, each experiment is repeated three times and the average value is obtained. Furthermore, a hot water bath is used to stabilize the temperature of nanofluid.

3. Artificial neural network (ANN)

Artificial neural networks (ANNs) are robust statistical approaches that try to be like the human nervous system by establishing a logical model consisting of inter-connective neurons in a computing network [10,11]. Neural networks are used to solve complex modeling challenges such as estimation, classification, and pattern recognition. Making an artificial neural network for modeling is of three steps. There are two main categories of ANNs which can be applied whether in regression or classification: the supervised and the unsupervised. In supervised, the network is trained by regulating the values of the weights between neurons which make it possible to assume output value(s) after taking delivery of a number of instructing data from previous experimental. In unsupervised, there is no desired target value while introducing inputs to the structure.

Multi-layer perceptron (MLP) feedforward neural network, one of the most popular training algorithms, usually has one or more hidden layers, in which selection of suitable numbers significantly depends upon the analyzer's experience and problem's nature. In the feedforward backpropagation algorithm, inputs pass through the network and at the end, outputs are compared with desired values and error is calculated [10,11].

The back propagation learning rule is for establishing a relationship between inputs and outputs that usually takes place by assigning random initial weights to input data and subsequently updating them by having a comparison between iterative network results and desired values. In different researches utilizing neural computations, a diversity of transfer functions were implemented depending upon problem complexity and nonlinearity. Two of the most types of transfer function which are common in recent engineering challenges are tangent sigmoid for hidden layers and linear functions for output layer. The reason for applying tangent sigmoid transfer functions for hidden neurons is getting an effective improvement in the input–output behavior when a little variation in updated weights happens. Fig. 1 shows a two layer neural network with one hidden layer consisting of nine neurons.

Termination of training networks takes place when either an error evaluation criterion like mean squared errors (MSE) and correlation coefficient (R) reaches a predefined acceptable extent or after passing pre-adjusted number of training epochs. The error measures include mean square error, and correlation coefficient is defined as follows [10,11]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(P_i - m_i)^2 \tag{1}$$

$$R = \frac{\sum_{i=1}^{n}(m_i-\overline{m})(p_i-\overline{p})}{\sqrt{\sum_{i=1}^{n}(m_i-\overline{m})^2\sum_{i=1}^{n}(p_i-\overline{p})^2}} \tag{2}$$

where m_i is the value of the experimental data, p_i is the predicted value, and n is the number of samples in the data set. $\overline{m}$ and $\overline{p}$ are the mean values of m and p, respectively.

4. Results and discussion

A multi-layer perceptron neural network has been used in which solid volume fraction and fluid temperature have been considered as network inputs for predicting thermal conductivity. Thermal conductivity has been measured in the following conditions, as shown in Fig. 2.

Solid volume fraction (φ): 0.0025, 0.005, 0.01, 0.02, 0.03, 0.04 and 0.05

Fluid temperature (T): 26, 35, 45, and 55 °C

In this work, out of 28 data obtained from experiments, 70% data are used for network training, while the remaining 30% data are used for network test and validation. Existence of input parameters in different

Table 1
Properties of Al_2O_3 nanoparticles.

Nanoparticle (Al_2O_3) purity	99.99%
Nanoparticle (Al_2O_3) APS	5 nm-very narrow particle size range
Nanoparticle (Al_2O_3) SSA/m^2g^{-1}	>150
Nanoparticle (Al_2O_3) morphology	Nearly spherical
Nanoparticle (Al_2O_3) color	White
Specific heat capacity/J kg^{-1} K^{-1}	880
Density/kg m^{-3}	3890
Bulk density/gmL^{-1}	0.18

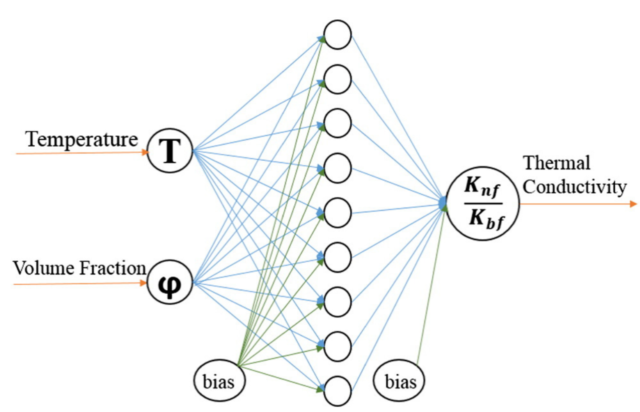

Fig. 1. Two layer neural network scheme.

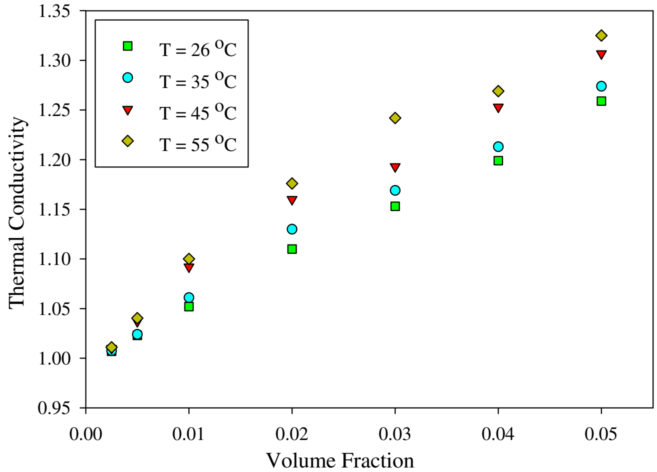

Fig. 2. Measured thermal conductivity for various solid volume fractions and fluid temperatures.

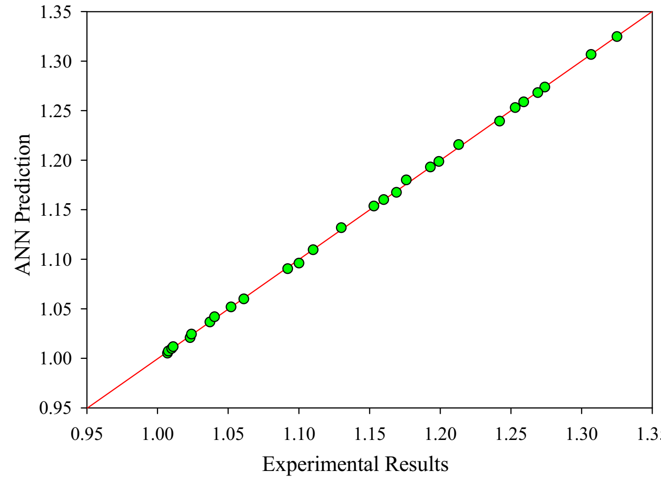

Fig. 3. Artificial neural network regression diagram.

ranges may cause inadequate network training. It is better to normalize data in [−1 1] interval to better network training. The number of optimal neurons in the hidden layer is determined trying different networks and comparing their performance functions. The neural network structure with the lowest MSE is considered as the most optimal network structure. Table 2 presents MSE and R values for artificial neural networks with different structures. According to Table 2, it is found out that the two structures with nine neurons in the hidden layer (Fig. 1) are the most optimal network structure for modeling thermal conductivity of Al_2O_3–water nanofluid in terms of temperature and volume fraction. This structure has been selected based on the smallest difference between model outputs and experimental results and predicts thermal conductivity. The MSE and correlation coefficient values for selected structure are equal to 2.42E−06 and 0.99988, respectively. Additionally, Fig. 3 shows network regression diagram after training whose value is over 0.999 in all cases. This regression value confirms good performance of the trained network.

In this study, experimental data have been used as correlation pattern for experimental results. Thermal conductivity of Al_2O_3–water nanofluid has been studied by developing non-linear regression equation including effect of solid volume fraction and fluid temperature. To select the best curve fitting equation, MSE and correlation coefficient were investigated for predicting thermal conductivity in terms of temperature and volume fraction from various equations. Based on the experimental data a correlation can be presented using the regression method. This correlation is a function of the temperature and volume fraction of nanofluids as follows:

$$\frac{k_{nf}}{k_{bf}} = 0.991 + 0.276T\varphi + 77.6\varphi^2 + 3641.231T\varphi^2 + \frac{0.00217}{\sin(T-\varphi)} - 6.01\times10^{-6}T^2 - 3647.099T\varphi\sin(\varphi) \tag{3}$$

where k_{nf}/k_{bf} represents thermal conductivity ratio of nanofluid and base fluid, φ and T are solid volume fraction and temperature of nanofluid, respectively. Performance of correction Eq. (3) has been presented in Table 3.

To visualize the prediction quality of the models used in this study, comparison through experimental results and models in different temperatures and volume fractions is presented in Fig. 4. It is clear in Fig. 4 that the predicted values for thermal conductivity of Al_2O_3/water nanofluid obtained through ANN and correlation in various temperatures and solid volume fractions agree with the measured data.

Conclusion

In this work, artificial neural network (ANN) and correlation were used to model thermal conductivity of Al_2O_3–water nanofluid for different temperatures and solid volume fractions. The mean squared error (MSE) of the ANN model prediction is only 2.42E−06;

Table 2
MSE and R values for various artificial neural network structures.

Number of hidden layers	Number of neurons in each hidden layer	R for train data	R for test data	R for validation data	R for all data	MSE	Maximum absolute error
1	2	0.99826	0.99899	0.99939	0.9981	3.72E−05	0.0127
1	3	0.99837	0.99976	0.99818	0.99843	3.22E−05	0.0123
1	4	0.9989	0.99884	0.99953	0.99899	2.05E−05	0.0087
1	5	0.99993	0.99009	0.99995	0.99842	1.80E−05	0.0129
1	6	0.99925	0.99953	0.99973	0.99926	1.53E−05	0.0128
1	7	0.99865	0.99945	0.99994	0.99869	2.85E−05	0.0212
1	8	0.99961	0.99996	0.99961	0.99963	7.91E−06	0.0053
1	9	0.9999	0.99995	0.99979	0.99988	2.42E−06	0.0041
1	10	0.99948	0.9998	0.9997	0.99957	1.05E−05	0.0027
2	2	0.99811	0.99894	0.99752	0.99805	2.47E−05	0.0083
2	3	0.99805	0.99214	0.99906	0.99759	9.93E−06	0.0031
2	4	0.99986	0.99927	0.99975	0.99971	6.58E−06	0.0035
2	5	0.99981	0.99925	1	0.99869	4.75E−06	0.0086
2	6	0.99744	0.99609	0.99803	0.99761	6.89E−06	0.0119
2	7	0.99961	0.99989	0.99977	0.99965	7.60E−06	0.0117
2	8	0.99984	0.99984	0.99992	0.99982	3.61E−06	0.0029
2	9	0.99968	0.99978	0.99998	0.99968	1.14E−05	0.0079
2	10	0.99749	0.99873	0.99954	0.99792	4.24E−05	0.0147

Table 3
Performance of correlation Eq. (3).

Mean square error	1.8866E − 05
Correlation coefficient	0.99909245
Maximum error	0.0154

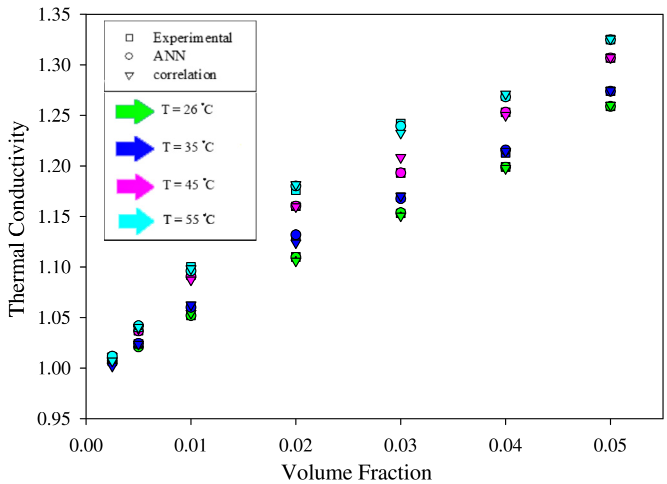

Fig. 4. Comparison between experimental results and predicted results from both models for various solid volume fractions and fluid temperatures.

and the correlation coefficient (R) is 0.99988. In addition, MSE and correlation coefficient for proposed correlation are 1.8866E − 05 and 0.9991, respectively. These prediction performances are considerably satisfactory, which suggest that the ANN model and correlation can be made applicable for modeling thermal conductivity of Al_2O_3–water nanofluid. However, ANN has a better performance than correlation.

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