Designing an artificial neural network to predict thermal conductivity and dynamic viscosity of ferromagnetic nanofluid

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1. Introduction

For many years, common fluids such as water, ethylene glycol, or oil have been used as the operating fluid in industry and engineering designs. The main problem is that the thermal conductivity of these fluids is small and thus the heat transfer rate is low. This is one of the limitations of this type of fluid that has led engineering design to have certain limitations. Recently, in order to increase the thermal conductivity of the fluid, nano-sized particles will be added to the fluid. In this way, the heat transfer of nanofluids within the enclosure and the influence of thermo-physical characteristics of nanofluids (such as thermal conductivity, thermal expansion coefficient, and dynamic viscosity) has been much studied \cite{1–5}.

In the last decade, several studies have been conducted on the thermal conductivity nanofluids. Wook Oh et al. \cite{6} presented experimental data on the thermal conductivity enhancement in Al\textsubscript{2}O\textsubscript{3} nanoparticle dispersed in DI water and EG as base fluids using the modified 3-omega \textsuperscript{(3\omega)} method. They showed that for DI water-based nanofluids, thermal conductivity incremental data agreed well with those of Wang et al. \cite{7}, which show higher increment compared to the results of Lee et al. \cite{8} and Das et al. \cite{9}. Also, they showed that EG-based nanofluids had relatively low thermal conductivity values compared with those of Lee et al. \cite{8} and Wang et al. \cite{7}. Experimental data on enhancement of thermal conductivity of ethylene glycol based silver nanofluids are reported by Sharma et al. \cite{10}. They illustrated thermal conductivity of silver nanofluids enhanced to \textsuperscript{10\%}, \textsuperscript{16\%}, and \textsuperscript{18\%} as the amounts of silver particles in nanofluid were \textsuperscript{1000}, \textsuperscript{5000}, and \textsuperscript{10000}, ppmm, respectively. The effect of solid volume fraction of ethylene glycol based copper oxide fluids is investigated by Lee et al. \cite{11}. Their experimental results demonstrated that these nanofluids, containing a small amount of nanoparticles, have significantly higher thermal conductivities than the same liquids without nanoparticles. In another study focusing on the solid concentration and shape of the nanoparticles, Xie et al. \cite{12} studied silicon carbide nanoparticles into two spherical and cylindrical forms added to water and ethylene glycol. They observed that the thermal conductivity is further increased when nanoparticles are cylindrical. Although many researchers have not considered the effect of temperature on thermal conductivity, recent studies show that nanofluids temperature effect on the properties of nanofluids is very important. Das et al. \cite{13} studied the behavior of CuO–water and Al\textsubscript{2}O\textsubscript{3}–water nanofluids with temperature. They concluded that with increasing temperature, the thermal conductivity of nanofluids increases. In another study, Karthik et al. \cite{14} investigated the thermal conductivity of CuO–DI water nanofluids experimentally. Their study also showed that temperature has a significant influence on the thermal conductivity of nanofluids.

To access the thermophysical characteristics of nanofluids in different concentrations, particle diameters, and temperatures, we need to do several experiments which are time consuming and expensive. In recent decade, in order to avoid such costs, there has been an interest in using soft computing methods to predict the behavior of nanofluids which are known as neural networks, fuzzy logic, and genetic algorithms. Among these, artificial neural networks are good tools to solve complex problems.
problems in different application with a considerable reduction in time and cost. However, there is a little reported work about modeling of thermal conductivity and viscosity of nanofluids using artificial neural network. In this regard, Mehrabi et al. [15] developed a model to predict the effective viscosity of nanofluids using an FCM-based adaptive neuro-fuzzy inference system (FCM-ANFIS) and a set of experimental data. They selected as the design parameters the size of the nanoparticles, volume concentration, and temperature to predict the effective viscosity of nanofluids. To model the viscosity, experimental data from literature were divided into two sets: a train and a test data set. The predicted viscosities were compared with experimental data for four nanofluids, which were Al2O3, CuO, TiO2, and SiO2, and with water as base fluid. The predicted results agreed with the experimental measurement.

An accurate and efficient artificial neural network based on genetic algorithm (GA) for predicting of nanofluids viscosity was developed by Karimi et al. [16]. They used genetic algorithm (GA) for optimizing the neural network parameters. Temperature and nanoparticle volume fraction were used as input data. The obtained results demonstrated that the GA-NN model was in good agreement with the experimental data. Papari et al. [17] used the neural network method to predict the thermal conductivity of different nanofluids, including single-walled carbon nanotubes in epoxy and polyethylene terephthalate and also multi-walled carbon nanotubes suspended in oil, decene, water, ethylene glycol. The comparisons between predicted and experimental data showed good agreement. Thermal conductivity modeling of γ-Al2O3, TiO2, and CuO nanoparticles in a 0.5 wt% of carboxymethyl cellulose (CMC) aqueous solution using a three-layer feed-forward neural network is exhibited by Højjat et al. [18]. They proposed neural network models to report the thermal conductivity as a function of the volume fraction of nanoparticles, temperature, and the thermal conductivity of the nanoparticles. Proposed models were in good agreement with the experimental values. Longo et al. [19] presented two neural network models for predicting the thermal conductivity of Al2O3–water and TiO2–water nanofluids by considering the temperature, volume fraction, nanoparticle diameter, and particle thermal conductivity as the input variables. Both models revealed that reasonable predicted data are in good agreement with the experimental data; but the 4-input model showed better performance. Recently, Hemmat Esfe et al. [20] modeled the thermal conductivity of MgO/EG nanofluids using experimental data and artificial neural network. Feedforward multilayer perceptron neural network was used to predict the thermal conductivity of the MgO/EG nanofluid. They considered the volume fraction, particle size, and temperature as the input data. The predicted results are in good agreement with the measured data.

Literature survey reveals that there is not any reported work about modeling of thermal conductivity and dynamic viscosity of Fe/EG nanofluids using artificial neural network (ANN). Therefore, in this work, ANN is designed using obtained experimental thermal conductivity and dynamic viscosity values of Fe/EG nanofluids depending on the different temperatures, diameters of particles, and volume fractions.

2. Architecture of artificial neural network

In complicated systems with several effective input parameters, artificial neural network (ANN) can predict output data. ANN is inspired from the human brain in order to process data and information. It includes integrated process units called neurons that can process input data. The multi-layer perceptron neural network includes input layer, hidden layer, and output layer. In this article, the ANN is used for modeling the behavior of Fe/EG nanofluid. The thermal conductivity and viscosity of Fe/EG nanofluid is modeled by ANN. The number of input parameters is three, which includes temperature (T), diameter of particles (d), and volume fraction (ϕ). Output values are the thermal conductivity (k) and dynamic viscosity (μ). The basic unit of neural network is the neuron. In each neuron, the sum of input values are weighted and added with a parameter called bias, and the sum is passed through a function which is called transfer function or activation function (see Fig. 1). The transfer function calculates the output of a neuron from its input. Some ANN includes several layers. Each layer includes several neurons and performs a simple process on data. In this ANN, the input dataset is divided into 3 sets randomly: train data, validation data, and test data. 70% of data set is regarded as train data. 15% of dataset is regarded as validation, and 15% of data is regarded for test data. During training process, the weight and biases of each neuron is generated. Validation data are used during training and it tunes parameters of classifier and defines stopping criteria also it prevents the network from over-fitting. Over-fitting occurs when the error on the training dataset reaches a very small value, but when new data are imported to the ANN, the new error is not small. It means that the ANN has memorized only the training examples, but the network is not able to generalize and predict new input values correctly. The test dataset shows how good the ANN is trained. In this simulation, the ANN includes two hidden layer and an output layer.

Feedforward multilayer perceptron neural network is used to predict the thermal conductivity enhancement and dynamic viscosity of the Fe/EG nanofluid. The first hidden layer includes seven neurons with tan-sigmoid transfer function (Eq. (1)). The second layer includes 5 neurons with the same previous transfer function.

\[ n_j = \frac{2}{1 + e^{-z}} - 1 \]  
\[ (1) \]

Where \( n_j \) is the output of the \( j \)-th neuron and \( z \) is given by

\[ z = \sum_{i=1}^{d} W_{ij} p_i + b_j \]  
\[ (2) \]

Where \( W_{ij} \) are the weights of connections from the \( i \)-th neurons in the previous layer to the \( j \)-th neurons, \( p_i \) denotes the output from the \( i \)-th neuron, \( b \) refers to the bias parameter, and \( r \) represents the number of neurons in the previous layer.

Finally, the output layer should have only two neurons because the number of outputs is two. The designed transfer function for output layer is linear. The number of input data is 72, which is extracted from experimental results. The selected learning algorithm is Levenberg Marquardt. In this network, during learning process, maximum number of iteration is 1000, maximum number of fail in validation check is 20, and the performance of network is mean square error (MSE). The value of MSE is calculated from Eq. (3).

\[ MSE = \frac{\sum_{i=1}^{n} (a_i - d_i)^2}{n} \]  
\[ (3) \]
Where $n$ is the number of data, $t_i$ denotes the $i$-th target value, and $a_i$ is the predicted value.

In some cases, ANN is not able to predict the output value precisely. In order to select the best architecture of ANN, different structures were used to obtain the optimal neural network which can predict data correctly. Different structures were made by permutation. Two limitations for the number of neurons were selected. The lower band was 10 and the upper band was 59. The proposed network is selected between 1675 different structures which were obtained by permutation. This optimum architecture was selected based on the smallest difference between predicted values (outputs of ANN) and experimental dataset. In order to decide which architecture is the best one and considering the fact that dividing input data into three main sets is random in each run of the program, to judge about output and performance of the network, it is better to consider a mean approximation after several iteration. Because the

Fig. 2. Proposed algorithm to find the optimal neural network.
data were randomly selected, for every structure, several times the network was run. In this work, this inner iteration is 20. After performing permutation, the best network architecture with highest accuracy and without over-fitting was selected. Comparing final results indicated that an ANN with 7 neurons in the first hidden layer and 5 neurons in the second hidden layer is the best architecture for predicting the thermal conductivity and viscosity of Fe-EG nanofluid by presented specifications. It can be seen that the network outputs have a very good agreement with experimental data. Both specification of Fe-EG nanofluid is predicted precisely. The proposed algorithm to find the optimal neural network is illustrated in Fig. 2.

3. Results and discussions

The artificial neural network which can predict thermal conductivity and dynamic viscosity of Fe/EG nanofluids from input experimental

![Fig. 3. Correlation between experimental values and predicted outputs for thermal conductivity. (a) training data set, (b) validation data set, (c) test data set.](image)

![Fig. 4. Comparison between experimental results and predicted outputs for thermal conductivity. (a) training data set, (b) validation data set, (c) test data set.](image)
data including temperature, diameter of particles, and volume fraction is designed. The experimental data set is divided into 3 main subsets including train, validation, and test. In the present study, the number of total experimental data were 72 which 50 of them is regarded as training data, 11 of them is considered as validation data and remain data referred to test data.

Fig. 3 shows correlation between experimental values and predicted thermal conductivity for training data set, validation data set and test data set. As can be observed, most of the data are on the bisector or in its vicinity which presents a proper correlation between experimental data and predicted outputs. This figure indicates the closeness among the experimental data and the predicted results using the ANN. In Fig. 3, the maximum error (error is difference between experimental and predicted values) and MSE are 2% and 0.00016, respectively. In addition, it is shown in Fig. 4 that there is a good agreement between experimental data and predicted results.

**Fig. 5.** Correlation between experimental values and predicted outputs for dynamic viscosity. (a) training data set, (b) validation data set, (c) test data set.

**Fig. 6.** Comparison between experimental results and predicted outputs for dynamic viscosity. (a) training data set, (b) validation data set, (c) test data set.
Fig. 7 illustrates the effect of solid volume fraction and temperature on the thermal conductivity and dynamic viscosity for different diameters of nanoparticles. In this figure, the adaptation of the neural network model on experimental results is clearly shown. As can be seen the fitted curve corresponds well with experimental results. The comparison between Fig. 7a and b reveal that ANN errors in the estimation of the thermal conductivity are lower than the dynamic viscosity which is confirmed by MSE value in Figs. 3 and 5.

It can be observed that the ANN is able to predict the thermal conductivity and dynamic viscosity accurately. Also, both of errors in predicting thermal conductivity and dynamic viscosity are small. This is due to the use of different number of neurons in different hidden layers to achieve an optimal network (see Fig. 2).

Following, due to lack of appropriate correlation to estimate the thermal conductivity and dynamic viscosity of Fe/EG nanofluid, based on ANN outputs, two sets of correlations with the same mathematical formula for different particle sizes are separately presented. In these correlations T and $\phi$ are temperature (°C) and solid volume fraction (%), respectively.

Eqs. (4) and (5) estimate respectively the thermal conductivity and dynamic viscosity of Fe/EG nanofluids as a function of the temperature and solid volume fraction. The constant values for different particle sizes are presented in Tables 1 and 2. The proposed correlations can be used in temperature ranging from 26 °C to 55 °C and volume fractions range of 0.125–3.0%.

To evaluate the accuracy of Eqs. (4) and (5), the comparisons among experimental data and results obtained by the Eqs. (4) and (5) are displayed in Figs. 8 and 9. These figures show that these correlations have very high accuracy. Also, calculations illustrate the maximum difference between the experimental results and correlations outputs is 2%. Consequently, these correlations can predict the thermal conductivity and dynamic viscosity of Fe/EG nanofluids at temperature ranging from 26 °C to 55 °C for solid volume fractions range of 0.125% to 3%.

\[
\frac{k_{nf}}{k_{bf}} = A + BT + CT^2 + \frac{D}{T} + E\phi + FFe^{2} + G(\frac{\phi}{T})^2 + H\phi^3
\]

\[
\frac{\mu_{nf}}{\mu_{bf}} = A + BT + CT^2 + \frac{D}{T} + E\phi + FFe^{2} + G(\frac{\phi}{T})^2 + H\phi^3
\]

4. Conclusion

The artificial neural network using 72 experimental data to predict thermal conductivity and dynamic viscosity of Fe/EG nanofluids is designed. Predicting is based on three input variables including temperature, diameter of particles, and volume fraction. The thermal conductivity and dynamic viscosity are regarded as ANN outputs. The main aim of ANN designing is reaching the smallest error in predicting thermal conductivity and dynamic viscosity of Fe/EG nanofluids.

**Table 1**

<table>
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<tr>
<th>$d_p$(nm)</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
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<td>$-6.1066 \times 10^{-5}$</td>
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<td>70</td>
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<td>$-6.0211 \times 10^{-5}$</td>
<td>5.5241</td>
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<td>$-0.0113$</td>
<td>$-7.1067$</td>
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**Table 2**

<table>
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<th>$d_p$(nm)</th>
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<th>C</th>
<th>D</th>
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<td>0.0194</td>
<td>5.2864</td>
<td>$-0.0057$</td>
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conductivity and dynamic viscosity of Fe/EG Nano fluids. ANN outputs showed that maximum error in predicting thermal conductivity and dynamic viscosity are 2% and 2.5%, respectively. Based on the ANN outputs, two sets of correlations for predicting the thermal conductivity and dynamic viscosity were proposed. The comparisons have been performed between experimental data with the proposed correlations in this study and it was found that the proposed correlations were in a well agreement with experimental data. The extension of the present work and other works [21–24] related to the heat transfer and thermophysical properties of nanofluid affords engineers a good option for nanofluid in applications like electronics, automotive, and nuclear applications where improved heat transfer or efficient heat dissipation is required.

Fig. 8. Comparison between experimental results and correlation outputs for thermal conductivity for different particle sizes. (a) 40 nm, (b) 70 nm, (c) 100 nm.

Fig. 9. Comparison between experimental results and correlation outputs for dynamic viscosity for different particle sizes. (a) 40 nm, (b) 70 nm, (c) 100 nm.
References


