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Using artificial neural network to predict thermal conductivity of ethylene glycol with alumina nanoparticle

Effects of temperature and solid volume fraction

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Abstract The correlations of thermal conductivity of alumina nanoparticle dispersed in pure ethylene glycol were proposed by neural network modeling using experimental data. The required input and target data have been taken from the experimental measurement to train artificial neural network (ANN). The temperatures were changed within 24–50 °C. Levenberg algorithm was used to train the ANN. Results showed that the thermal conductivity of nanofluid had a significant increase with increasing solid volume fraction of nanoparticles. The results also revealed that the ANN model can predict the thermal conductivity of Al_2O_3–EG nanofluid accurately with maximum deviation of 1.3 % and high correlation coefficient ($R > 0.998$).

Keywords Thermal conductivity correlation · Artificial neural network · Al_2O_3–EG nanofluid · Solid volume fraction

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Introduction

In the last decade, heat transfer enhancement through nanofluids has been an interesting topic from many researchers. Among them, the thermal conductivity of the nanofluid is an important factor to evaluate the thermal performance of nanofluid. Many theoretical and experimental studies have been employed to estimate the thermal conductivity of nanofluid. For example, Hemmat Esfe et al. [1–4] performed some studies on thermophysical properties of nanofluid experimentally. Khanafer and Vafai [5] presented a comprehensive numerical study on thermophysical characteristics of nanofluids. Also, applications of nanofluids in solar energy [6, 7] and heat exchangers [8–10] are considered by some researchers. Besides these studies, some review articles concluded the researches which have done about the properties of various nanofluids [11, 12]. Nevertheless, there is not any comprehensive model to predict the thermal conductivity of nanofluid in the open literature.

Hemmat Esfe et al. [13] investigated experimentally the thermal conductivity of water-based nanofluid with Al_2O_3 suspensions and presented a correlation as a function of temperature and solid volume fraction of nanoparticles using experimental data. Their results revealed that the thermal conductivity is more sensitive to solid volume fraction for a case with a higher temperature. In another experimental study [14], they studied the effect of nanoparticle volume fraction on thermal conductivity and dynamic viscosity of Ag–MgO/water hybrid nanofluid. New correlations as a function of nanoparticle volume fraction were proposed. Also, according to their results, the thermal conductivity and dynamic viscosity of nanofluid increase with nanoparticle volume fractions. Barbés et al. [15] investigated the thermal properties of CuO dispersed

in water and ethylene glycol as a function of the particle volume fraction and temperature. Their results indicated that thermal conductivities can be well justified using a classical model (Hamilton–Crosser), and experimental measurements of heat capacities can be justified with a model of particles in thermal equilibrium with the base fluid.

Recently, an artificial neural network (ANN) has been employed by many researchers as an accurate tool to model the thermophysical properties of various fluids. Eslamloueyan and Khademi [16] developed a neural network-based model to predict the thermal conductivity of pure gases at atmospheric pressure as a function of temperature. Their variables were temperature, molecular weight and critical pressure. They concluded that the best architecture of the feed-forward network can be obtained by using trial-and-error method. Their results indicated that the proposed ANN model can predict thermal conductivity of pure gases with a relatively lower error than that of other correlations. Hemmat Esfe et al. [17], based on experimental data, modeled the thermal conductivity of Cu–TiO_2/EG–water nanofluids using ANN. Their results indicated that an artificial neural network model had great ability to predict thermal conductivity of nanofluid and excellent agreement with the experimental results. They also employed an artificial neural network to predict the thermal conductivity of ZnO–EG nanofluid and dynamic viscosity of ferromagnetic nanofluid in others researches [18, 19].

Furthermore, other modeling methods such as design of experiments and genetic algorithm are used to predict and optimize different properties of nanofluids. Hemmat Esfe et al. [20] performed experimental design in order to evaluate the temperature and solid volume concentrations on thermal conductivity of CNTs–Al_2O_3/water hybrid nanofluids. They used two-level full factorial design to investigate the effect of solid volume fraction of nanoparticles and temperatures on thermal conductivity of nanofluid. They presented new correlation based on experimental data with high accuracy to predict the thermal conductivity of CNTs–Al_2O_3/water nanofluids. Karimi et al. [21] employed artificial neural network–genetic algorithm (ANN–GA) to propose new correlation of density of nanofluids. In another study, optimization of stability parameters for titanium dioxide nanofluid was investigated by using response surface methodology and artificial neural networks from Sadollah et al. [22].

The main purpose of this work is employing an artificial neural network to correlate the thermal conductivity of Al_2O_3–EG nanofluid over a wide range of temperatures and solid volume fractions of nanoparticles. The network inputs are the solid volume fraction of nanoparticles and temperatures.

Preparation of nanofluid

In the present study, the thermal conductivity of Al_2O_3–EG nanofluid at different solid volume fractions and temperatures was measured by using KD2 Pro instrument. The Al_2O_3–EG nanofluid was prepared by two-step method. Different solid volume fractions of nanofluid including 5.0, 4.0, 3.0, 2.0, 1.0, 0.75, 0.5 and 0.2 % were produced by mixing pure EG and Al_2O_3 nanoparticles with average size of 5 nm. After adding nanoparticles to EG, a magnetic mixer is utilized to mix the alumina and ethylene glycol for about 1 h. Then, the suspensions were inserted in the ultrasonic processor (400 W, 24 kHz) for 8–9 h. This method can break down the agglomeration between the particles and also prevent the sedimentation to obtain a uniform dispersion and a stable suspension. Figure 1 shows the sample of Al_2O_3–EG nanofluid and pure EG (Merck). All measurements were taken 1 day after preparation of nanofluids. During this time, no sedimentation is observed.

The architecture of an artificial neural network

The modeling technique is the artificial neural network (ANN) which consists of an interconnected group of artificial neurons; each of them receives one or more inputs and sums them to produce an output. It can be highly inspired by human brain in processing data. One of its parts, i.e., neurons, is responsible for processing data. The multi-layer perceptron neural network can divided into three layers: input layer, hidden layer and output layer. After data set is collected, input variables, i.e., model's independent variables, are selected. The available correlations for the thermal conductivity of nanofluid can be

Fig. 1 Samples of pure EG and Al_2O_3–EG nanofluids

Table 1 Summary of relative thermal conductivity of nanofluid

T/°C	φ							
	0.2	0.5	0.75	1	2	3	4	5
24	1.009	1.027	1.058	1.063	1.127	1.180	1.196	1.283
30	1.011	1.029	1.062	1.065	1.149	1.222	1.235	1.307
35	1.013	1.031	1.063	1.075	1.158	1.226	1.259	1.332
40	1.015	1.032	1.066	1.082	1.177	1.232	1.283	1.352
45	1.0176	1.0341	1.0661	1.093	1.185	1.25	1.291	1.397
50	1.019	1.036	1.069	1.107	1.207	1.288	1.312	1.410

described as a function of temperature and solid volume fraction as follows:

$$\frac{k_{\mathrm{nf}}}{k_{\mathrm{bf}}} = f(T, \varphi) \tag{1}$$

In the present study, the input parameters consist of temperature (T) and solid volume fraction (φ) and the output parameter is the relative thermal conductivity ($k_{\mathrm{nf}}/k_{\mathrm{bf}}$) of alumina–EG nanofluid. Table 1 summarizes the relative thermal conductivity values used as inputs. The number of input data is 48 which are measured by KD2 Pro instrument.

In the next step, the artificial neural network architecture should be developed. A network with two hidden layers was selected as the starting network structure. A constructive approach was utilized to determine the number of neurons in the hidden layer [23]. According to this approach, a few neurons are used in the hidden layer, and if the trained network error does not meet the desired tolerance, the number of neurons in the hidden layer is increased by one and training cycle and performance evaluation are repeated. This procedure goes on until the trained network performance is satisfactory.

Table 2 Specification of parameters in best structure of network

MSE	4.86E−05
MAE	0.0049
Test performance	1.46E−04
Training performance	8.464E−06
Valid performance	1.47E−04
R	0.9982

The feed-forward network was trained by Levenberg–Marquardt algorithm [24]. Applying the constructive approach to design the neural network model for the prediction of thermal conductivity led to a three-layer network with two neurons in input layer, three neurons in the first hidden layer, five neurons in second hidden layer and one neuron at output layer. Figure 2 shows the best configuration of the neural network to predict the thermal conductivity of Al_2O_3–EG nanofluid.

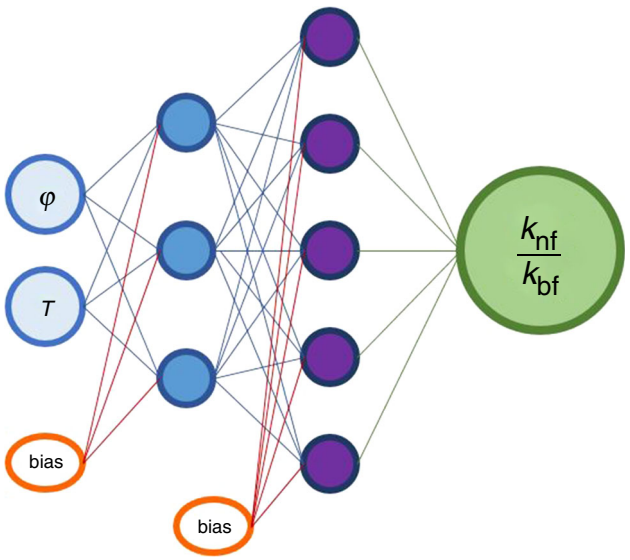

Fig. 2 The best configuration of the neural network to predict the thermal conductivity of Al_2O_3–EG nanofluid

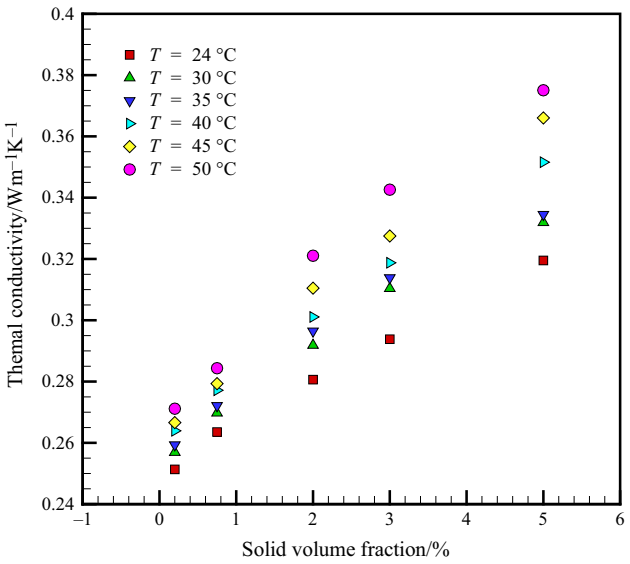

Fig. 3 Thermal conductivity of Al_2O_3–EG versus solid volume fraction for different temperatures

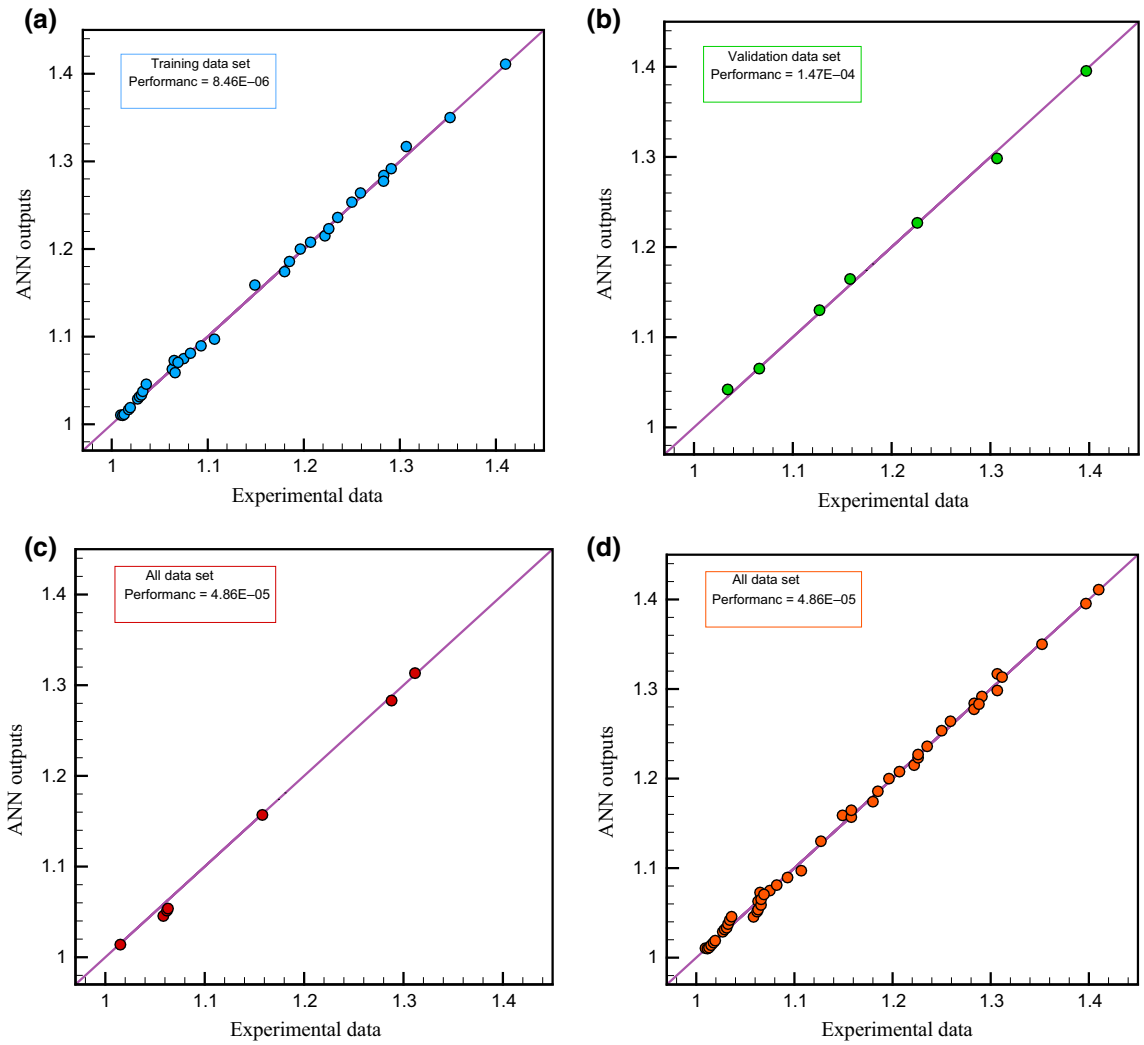

Fig. 4 Correlations between experimental data and ANN outputs for relative thermal conductivity. **a** Training data set, **b** validation data set, **c** test data set and **d** all data set

Training, validation and test data sets errors can be used for the approximate estimation of a trained network performance. However, it can be useful to examine the network response completely. Regression analysis was performed for the evaluation of the network capability for conductivity prediction. The regression coefficient (R) was used as a criterion to evaluate how the trained network estimation is in agreement with the experimental data. Also, different neural network structures were compared using their mean square errors (MSE) and mean absolute errors (MAE). The MSE and MAE are defined as follows:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\left.\frac{k_{\mathrm{nf}}}{k_{\mathrm{bf}}}\right|_{\mathrm{Exp}} - \left.\frac{k_{\mathrm{nf}}}{k_{\mathrm{bf}}}\right|_{\mathrm{net}}\right)^2$$
$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\left.\frac{k_{\mathrm{nf}}}{k_{\mathrm{bf}}}\right|_{\mathrm{Exp}} - \left.\frac{k_{\mathrm{nf}}}{k_{\mathrm{bf}}}\right|_{\mathrm{net}}\right| \quad (2)$$

where k_{nf} represents the thermal conductivity of nanofluid, k_{bf} is the thermal conductivity of base fluid, and n is the number of data points. Table 2 discloses the performance functions (MSE, MAE and regression values) for the optimal network. As can be observed, the value of regression coefficient and mean square error (MSE) is 0.9982 and 4.86E−05, respectively. It is concluded that the structure of network is appropriate to model the thermal conductivity of nanofluid.

Results and discussion

In this work, experimental data were used to predict the relative thermal conductivity of Al_2O_3–EG nanofluid. Experimental measurements consist of six temperatures (24, 30, 35, 40, 45 and 50 °C) and eight solid volume

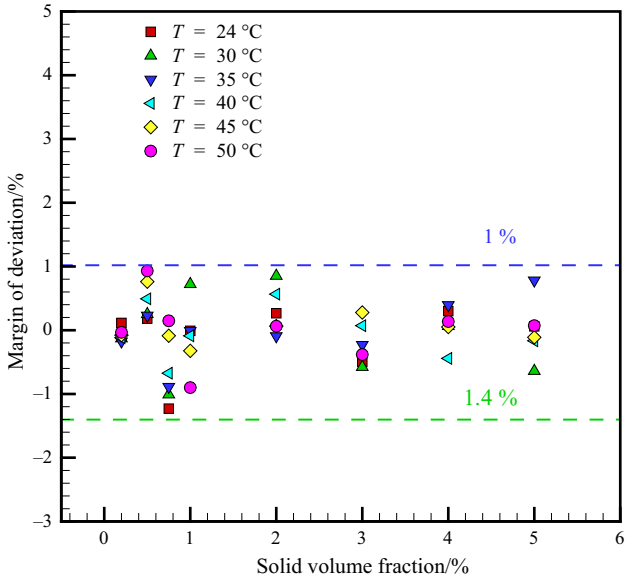

Fig. 5 Margin of deviation of the ANN outputs versus solid volume fraction

fractions. Figure 3 shows the thermal conductivity of Al_2O_3–EG nanofluid in terms of solid volume fractions in various temperatures. Measurements reveal that thermal conductivity enhances with increasing temperature and concentration of nanoparticles. This increase could be due to increase in interactions among the particles and Brownian motion [25]. Also, the effects of solid volume fraction on thermal conductivity are more significant than the temperature.

The results indicate that using alumina nanoparticles can improve the thermal conductivity of base fluid (ethylene glycol). Also, it is evident that the maximum enhancement in thermal conductivity is almost 41 % at $T = 50$ °C and solid volume fraction of 5 %. If this result is compared with the results of thermal conductivity of Al_2O_3–water nanofluid that was performed by Hemmat Esfe et al. [13], then they obtained the maximum increase in thermal conductivity equal to 32.5 % at the same conditions (solid volume fraction of 5 % and $T = 50$ °C). Therefore, it can be concluded that the role of base fluid is important to thermal conductivity of nanofluid.

Figure 4 shows the correlations between experimental data and ANN outputs of relative thermal conductivity for training data set, validation data set and test data set. As can be seen from this figure, all data sets are around the bisector. This indicates that neural networks can predict thermal conductivity of alumina–EG nanofluid with very little difference from experimental data. It is noted that the maximum errors (errors are difference between experimental and predicted values) of training outputs, validation and test outputs are 0.01028, 0.00831 and 0.00178, respectively.

Training data set is important to get the best artificial neural network. The number of data sets that are utilized in training network is more than that of validation and test data sets. In this study, 75 % of data are allocated to training network. As can be observed, these data are chosen from all ranges of experimental results randomly from ANN.

All data set results are shown in Fig. 4d. The MSE value is calculated from this figure. The comparison between the ANN outputs and experimental data illustrates that the mean square error is equal to 4.86E−05. Therefore, a reasonable agreement in predicting values and experimental data is observed.

To confirm the accuracy of the ANN modeling, the margin of deviation (MOD) can be defined as follows:

$$\mathrm{MOD}\,(\%) = \frac{k_{\mathrm{net}} - k_{\mathrm{exp}}}{k_{\mathrm{net}}} \times 100 \qquad (3)$$

where k_{net} and k_{exp} show the thermal conductivity obtained through the network and experimental results, respectively. The margin of deviation in terms of solid volume fractions at various temperatures is shown in Fig. 5. As can be observed, the maximum deviation of the neural network outputs is less than 1.4 %. It is concluded that the artificial neural network (ANN) modeling has acceptable accuracy to estimate the thermal conductivity of Al_2O_3–EG.

Conclusions

In the present study, the correlations of the thermal conductivity of Al_2O_3–EG nanofluid were proposed by using an artificial neural network (ANN). To predict the relative thermal conductivity of alumina–EG with artificial neural network, 48 data sets were used as a function of temperature and solid volume fraction of nanoparticles. The feed-forward multi-layer network was utilized for ANN modeling. The results showed that the ANN model could estimate the relative thermal conductivity as a function of the nanoparticle concentrations and the temperatures. The results indicated that the artificial neural network due to the high correlation coefficient between output of ANN and experimental values is an accurate tool to modeling the thermal conductivity of nanofluid.

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References

1. Hemmat Esfe M, Saedodin S, Wongwises S, Toghraie D. An experimental study on the effect of diameter on thermal conductivity and dynamic viscosity of Fe/water nanofluids. J Therm Anal Calorim. 2015;119:1817–24. doi:10.1007/s10973-014-4328-8.
2. Hemmat Esfe M, Arani AAA, Rezaie M, Yan WM, Karimipour A. Experimental determination of thermal conductivity and dynamic viscosity of Ag–MgO/water hybrid nanofluid. Int Commun Heat Mass Transf. 2015;66:189–95.
3. Hemmat Esfe M, Saedodin S, Yan WM, Afrand M, Sina N, Study on thermal conductivity of water based nanofluids with hybrid suspensions of CNTs/Al_2O_3 nanoparticles. J Therm Anal Calorim. 2016;124(1):455–460. doi:10.1007/s10973-015-5104-0.
4. Hemmat Esfe M, Saedodin S, Asadi A, Karimipour A. Thermal conductivity and viscosity of Mg $(OH)_2$-ethylene glycol nanofluids. J Therm Anal Calorim. 2015;120:1145–9.
5. Khanafer K, Vafai K. A critical synthesis of thermophysical characteristics of nanofluids. Int J Heat Mass Transf. 2011;54(19–20):4410–28.
6. Mahian O, Kianifar A, Kalogirou SA, Pop I, Wongwises S. A review of the applications of nanofluids in solar energy. Int J Heat Mass Transf. 2013;57(2):582–94.
7. Mahian O, Kianifar A, Sahin AZ, Wongwises S. Performance analysis of a minichannel-based solar collector using different nanofluids. Energy Convers Manag. 2014;88:129–38.
8. Hemmat Esfe M, Saedodin S. Turbulent forced convection heat transfer and thermophysical properties of Mgo–water nanofluid with consideration of different nanoparticles diameter, an empirical study. J Therm Anal Calorim. 2015;119(2):1205–13.
9. Hemmat Esfe M, Naderi A, Akbari M, Afrand M, Karimipour A. Evaluation of thermal conductivity of COOH-functionalized MWCNTs/water via temperature and solid volume fraction by using experimental data and ANN methods. J Therm Anal Calorim. 2015;121:1273–6.
10. Hemmat Esfe M, Saedodin S, Mahian O, Wongwises S. Heat transfer characteristics and pressure drop of COOH-functionalized DWCNTs/water nanofluid in turbulent flow at low concentrations. Int J Heat Mass Transf. 2014;73:186–94.
11. Celen A, Çebi A, Aktas M, Mahian O, Dalkilic AS, Wongwises S. A review of nanorefrigerants: flow characteristics and applications. Int J Refrig. 2014;44:125–40.
12. Chandrasekar M, Suresh S, Senthilkumar T. Mechanisms proposed through experimental investigations on thermophysical properties and forced convective heat transfer characteristics of various nanofluids—a review. Renew Sustain Energy Rev. 2012;16(6):3917–38.
13. M. Hemmat Esfe, S. Saedodin, O. Mahian, and S. Wongwises, Thermal conductivity of Al2O3/water nanofluids: measurement, correlation, sensitivity analysis, and comparisons with literature reports, J Therm Anal Calorim., 117 (2014), pp. 675–681.
14. M. Hemmat Esfe, S. Saedodin, M. Bahiraei, D. Toghraie, O. Mahian, and S. Wongwises, "Thermal conductivity modeling of MgO/EG nanofluids using experimental data and artificial neural network," *J. Therm. Anal. Calorim.*, 118 (1) (2014) pp. 287–294.
15. Barbés B, Páramo R, Blanco E, Casanova C. Thermal conductivity and specific heat capacity measurements of CuO nanofluids. J Therm Anal Calorim. 2014;115(2):1883–91.
16. Eslamloueyan R, Khademi MH. Estimation of thermal conductivity of pure gases by using artificial neural networks. Int J Therm Sci. 2009;48:1094–101.
17. Hemmat Esfe M, Wongwises S, Naderi A, Asadi A, Safaei MR, Rostamian H, Dahari M, Karimipour A. Thermal conductivity of Cu/TiO_2–water/EG hybrid nanofluid: experimental data and modeling using artificial neural network and correlation. Int Commun Heat Mass Transf. 2015;66:100–4.
18. Hemmat Esfe M, Saedodin S, Naderi A, Alirezaie A, Karimipour A, Wongwises S, Goodarzi M. Modeling of thermal conductivity of ZnO–EG using experimental data and ANN methods. Int CommunHeat Mass Transf. 2015;63:35–40.
19. M. Hemmat Esfe, S. Saedodin, N. Sina, and M. Afrand, Designing an artificial neural network to predict thermal conductivity and dynamic viscosity of ferromagnetic nanofluid, Int. Commun. Heat Mass Transf., doi:10.1016/j.icheatmasstransfer.2015.06.013.
20. Hemmat Esfe M, Saedodin S, Biglari M, Rostamian H. Experimental investigation of thermal conductivity of CNTs-Al_2O_3/water: a statistical approach. Int Commun Heat Mass Transf. 2015;69:29–33.
21. Karimi H, Yousefi F. Application of artificial neural network–genetic algorithm (ANN–GA) to correlation of density in nanofluids. Fluid Phase Equilib. 2012;336:79–83.
22. Sadollah A, Ghadimi A, Metselaar IH, Bahreininejad A. Prediction and optimization of stability parameters for titanium dioxide nanofluid using response surface methodology and artificial neural networks. Sci Eng Compos Mater. 2013;20:319–30.
23. S. Haykin, "Adaptive filters," Signal Process. Mag., vol. 6, 1999.
24. Marquardt DW. An algorithm for least-squares estimation of nonlinear parameters. J Soc Ind Appl Math. 1963;11:431–41.
25. Hemmat Esfe M, Saedodin S, Akbari M, Karimipour A, Afrand M, Wongwises S, Safaei MR, Dahari M. Experimental investigation and development of new correlations for thermal conductivity of CuO/EG–water nanofluid. Int Commun Heat Mass Transf. 2015;65:47–51.