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Designing an artificial neural network using radial basis function (RBF-ANN) to model thermal conductivity of ethylene glycol–water-based TiO_2 nanofluids

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Abstract In this article, thermal conductivity of ethylene glycol–water-based TiO_2 nanofluids has been modeled by artificial neural network. For this purpose, thermal conductivity of nanofluids with volume fractions of 0.2–1 % has been collected in temperatures of 30–70 °C. These data were modeled by artificial neural networks. So two common types of neural networks were used, and the results were compared with each other. One of these networks was multilayer perceptron, and the other one was radial basis approximation. Finally, an experimental relationship was suggested for calculating thermal conductivity of this nanofluid and the results were compared with the results of radial basis neural network. This comparison shows that neural networks are very powerful in modeling the nanofluids experimental data and are able to follow the patterns of these data with a high precision.

Keywords Thermal conductivity · Artificial neural network · Temperature · Modeling

Introduction

Heat transfer in industrial equipment is a subject that has been studied for several decades. It is significant since if the produced heat is not removed by industrial equipment, the device will stop operating and there will often be serious damage to it. One way to increase heat transfer in cooling systems is using fluids with high heat transfer rates. Therefore, researchers are getting interested in the capacity found in nanofluids. Nanofluids are fluids containing nanoparticles of 1–100 nm. These particles can be oxide, metal, carbon, and ceramic.

Various factors affecting nanofluids thermal conductivity have been mentioned in different reports [1]. The effect of different factors on heat transfer, mass, and nanofluids viscosity has been investigated in different articles. The method of nanofluids preparation is one of these factors. Some believe that nanofluids preparation is the key step in using nanoparticles for increasing fluids thermal conductivity [2]. Nanofluids preparation can occur in one or two steps. In the one-step technique, nanoparticles are directly suspended in base fluid. This technique is generally used for the preparation of metal fluids, otherwise metal nanoparticles oxidize. The disadvantage of this technique is nanofluids preparation in small volume and very low densities [3, 4]. The second technique for nanofluids preparation is the two-step technique [5–13]. In this technique, powder nanoparticles are suspended in base fluid by using surfactant and sonication [14–21].

Another parameter affecting nanofluids preparation and their viscosity and thermal conductivity is using surfactants. Almost all nanoparticles must be used with surfactants or changes must be exercised in their surface through functionalization so that they can be suspended in the fluid. These surfactants may be cationic or anionic. In some cases, the effect of surfactant on thermal conductivity and viscosity cannot be ignored and their effects have been mentioned in researches. Estelle et al. [22] in their study investigated the effect of different surfactants on viscosity and thermal conductivity of carbon nanotube nanofluids. For this purpose, SDBS and Lignin surfactants have been compared with each other. Lignin both gives non-Newtonian property of shear thinning and produces a higher thermal conductivity in nanofluid compared to SDBS. Also,

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Xia et al. [23] have investigated the effect of PVP and SDS surfactants on thermal conductivity of base fluid and Al_2O_3-water nanofluids. They indicated that nanofluids containing SDS have higher thermal conductivity. They have also studied the effect of these surfactants volume fraction on thermal conductivity of alumina-water nanofluids.

In addition to experimental researches, some researchers are involved in numerical and statistical investigations of nanofluids. Hemmat Esfe et al. [24–29] have reported using different types of artificial neural networks in different articles. It is concluded from all these articles that artificial neural network is considered a proper tool for modeling nanofluids behavior. It has also been conducted by some other researchers. Hojjat et al. [30] have modeled three types of non-Newtonian nanofluids by using neural networks and compared them with experimental data and theoretical models.

One of the problems of different applications of nanofluids is lack of reliable models with required thermophysical properties to be used in technical and engineering designs. The vast amount of experimental data, different methods of data collecting, and a large number of considerations and differences existing in the results of experimental researches bring about confusion in using nanofluids. Researchers are more involved in conducting experimental measurements and reporting their results than in considering the collection and presentation of models regarding nanofluids thermophysical properties as a tool needed for engineers. The huge amount of the experimental data presented in different resources has not been collected and presented accurately.

In this article, the experimental data of thermal conductivity of TiO_2 nanofluids have been modeled by using artificial neural networks in radial basis approximation method and the results of this modeling have been compared with experimental data and theoretical model suggested by Hashin and Shtrikman.

The experimental data of thermal conductivity [31] of ethylene glycol–water-based TiO_2 nanofluid have been modeled by using neural network in radial basis approximation method. A review of previous researches shows despite various applications of this nanofluid, a coherent study has not been conducted on modeling thermal conductivity of this nanofluid so far. Also, these data have been given as inputs to two separate neural networks and modeled by these two networks and the suggested models have been compared in terms of precision and extent.

Experimental data

Thermal conductivity data are obtained from [31] which measured using apparatus supplied by P.A. Hilton, UK. The apparatus is capable of measuring the thermal conductivity of nanofluids. The apparatus has built-in control unit to regulate heat supplied to the test samples.

Artificial neural network

The sciences related to artificial neural networks are progressing rapidly and are employed in different fields. Artificial neural networks have been modeled from human brain networks. That is why they possess the unique features of brain processing. Increase in speed and high sensitivity to errors can be mentioned as two of their features.

When the inputs to software programs change, one does not expect to receive a response from them, while the brain may present a suitable response in a new situation despite lack of a specific experience.

It is evident that neural network obtains its computational power first from its extensive parallel structure and then from the ability of learning and generalization. Generalization means that neural network creates acceptable outputs for the inputs with which they have not encountered during training. These two abilities of information processing make it possible for the neural network to respond to complicated and large-scale issues that could not be investigated. Nevertheless, neural networks alone cannot solve all problems. The stable system must be combined with an engineering method. For this purpose, different types of neural network structures are tested and employed and the best network in terms of precision and error value is selected. By using neural networks, the complicated behaviors of different types of phenomena can be modeled and used for predicting the results of similar phenomena.

In this article, two structures of neural networks have been used for modeling the thermal conductivity data of ethylene glycol–water-based TiO_2 nanofluids. The first structure of neural network shown in Fig. 1 has two hidden layers, each of which includes five neurons. The transfer function of the first layer is radial basis function, and the transfer function of the second layer is tangent sigmoid. After investigating different structures with different numbers of neurons, this structure turned out to have the best performance. Regression coefficient and mean-squared error (MSE) for these structures have been presented in Table 1. In order to train the neural network, two train functions have been used. Trainlm transfers input data to neural network pattern with a higher speed, and trainbr (Bayesian regulation train function) does this process with a higher precision. As observed in Table 1, the regression coefficient of the network trained by trainbr function is greater and becomes convergent sooner.

The regression coefficient of the selected structure is 0.9999. A value higher than this is not expected. Therefore, at this point testing, different structures have stopped.

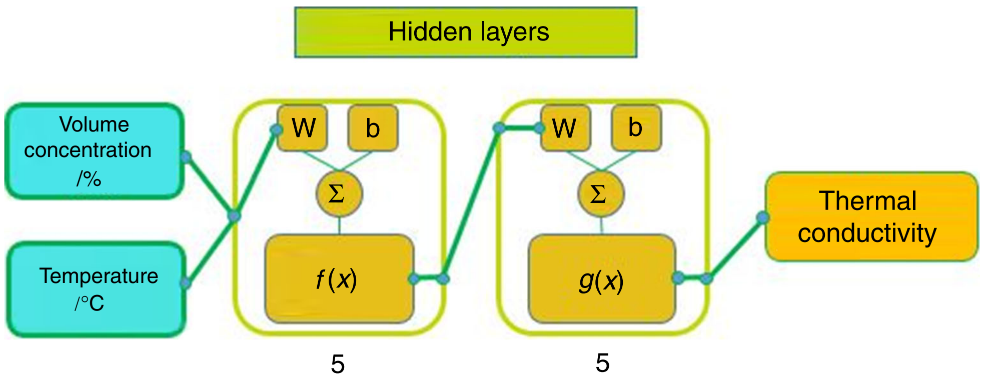

Fig. 1 First structure of neural network

Table 1 Regression parameters of different ANN structures

Neurons	Train function	*R*	MSE	Train performance	Test performance
[1 1]	Trainlm	0.9416	2.5432e−5	2.9031e−5	1.6568e−5
	Trainbr	0.9367	2.6970e−5	2.6056e−5	3.1540e−5
[2 2]	Trainlm	0.9979	9.2129e−7	9.2436e−7	7.7166e−7
	Trainbr	0.9983	7.6153e−7	7.2137e−7	9.6234e−7
[3 3]	Trainlm	0.9987	6.0705e−7	3.7271e−7	1.5742e−6
	Trainbr	0.0.9995	2.1370e−7	2.0639e−7	2.5026e−7
[4 4]	Trainlm	0.9984	8.3121e−7	1.8002e−7	2.8984e−6
	Trainbr	0.9998	4.9596e−8	9.2449e−9	2.5135e−7
[5 5]	Trainlm	0.9936	3.1608e−6	4.0388e−7	9.2125e−6
	Trainbr	0.9999	4.8063e−8	9.8657e−9	2.3905e−7

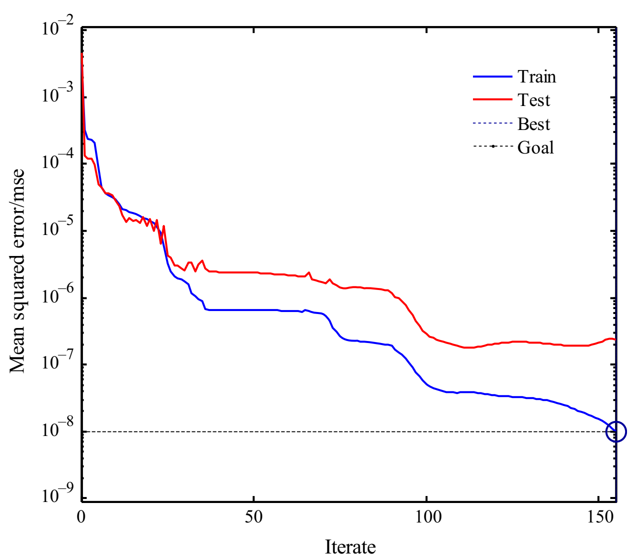

Fig. 2 Performance of neural network for train and test data

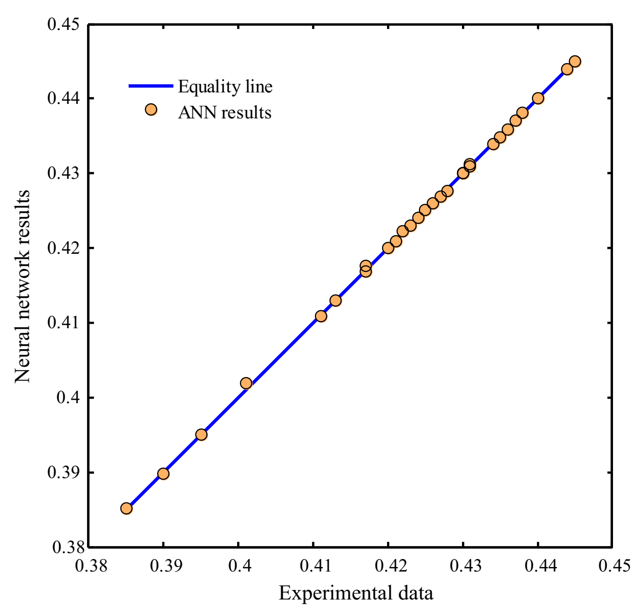

Fig. 3 Regression of neural network modeling

Along with neural network training, MSE values for training and test data in terms of iterations are recorded. These values are shown in Fig. 2. Due to using learning algorithm of Bayesian regulation back propagation, no data are devoted to validation, so the data are divided into two groups of train and test data. Another advantage of using trainbr transfer function is that an acceptable goal is determined for MSE value and the network continues iterations to achieve the goal and the operation of iteration stops as soon as the goal is achieved. The goal specified for the performance is 10^{-8} that has been achieved.

Figure 3 shows the regression of the modeled data. In this diagram, neural network outputs have been drawn in terms of experimental data. The adjustment of neural network outputs with the bisector shows the success of neural network in modeling the data and the network high precision.

Radial basis approximation

The second section of modeling has been conducted by radial basis approximation. Figure 4 shows the diagram of radial basis function.

This modeling, without being required to test different networks with different structures, starts learning automatically in order to determine the desired goal for MSE. For this purpose, different structures are tested and if an acceptable result is not obtained, it adds one neuron to the structure and restarts the modeling. The final structure of modeling the data is shown in Fig. 5.

The goal specified for MSE is 10^{-8} like the first structure to check with how many neurons the network can obtain a performance equal to the first network. This goal has been achieved with 25 neurons. In Table 2, the number of neurons in the hidden layer and the performance of system for each structure are observed.

Figure 6 shows a comparison between the results of neural network modeling and experimental data. As is

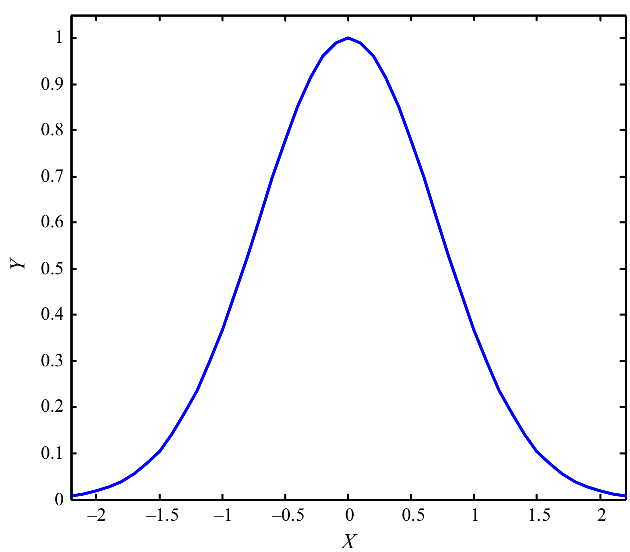

Fig. 4 Radial basis function

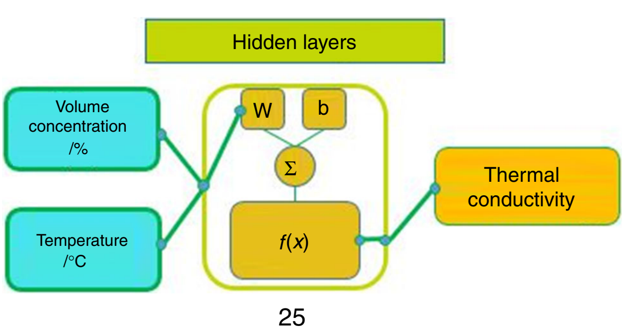

Fig. 5 Structure of radial basis approximation

Table 2 Values obtained for MSE for each structure in neural network

Neurons	MSE	Neurons	MSE
1	0.000217382	14	1.85585e−05
2	0.000173363	13	2.78837e−05
3	0.000163203	15	6.13974e−06
4	0.00015606	16	4.57595e−06
5	6.72265e−05	17	3.08116e−06
6	6.41487e−05	18	1.94295e−06
7	5.63928e−05	19	8.3355e−07
8	5.22111e−05	20	7.80983e−07
9	4.69021e−05	21	4.14174e−07
10	4.06106e−05	22	3.74929e−07
11	3.59518e−05	23	3.21945e−07
12	2.96372e−05	24	3.19438e−07
		25	2.66731e−08

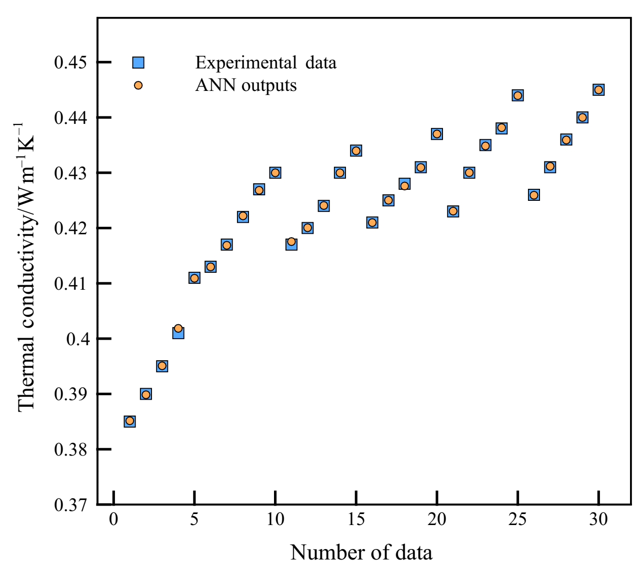

Fig. 6 Comparison between ANN model and experimental data

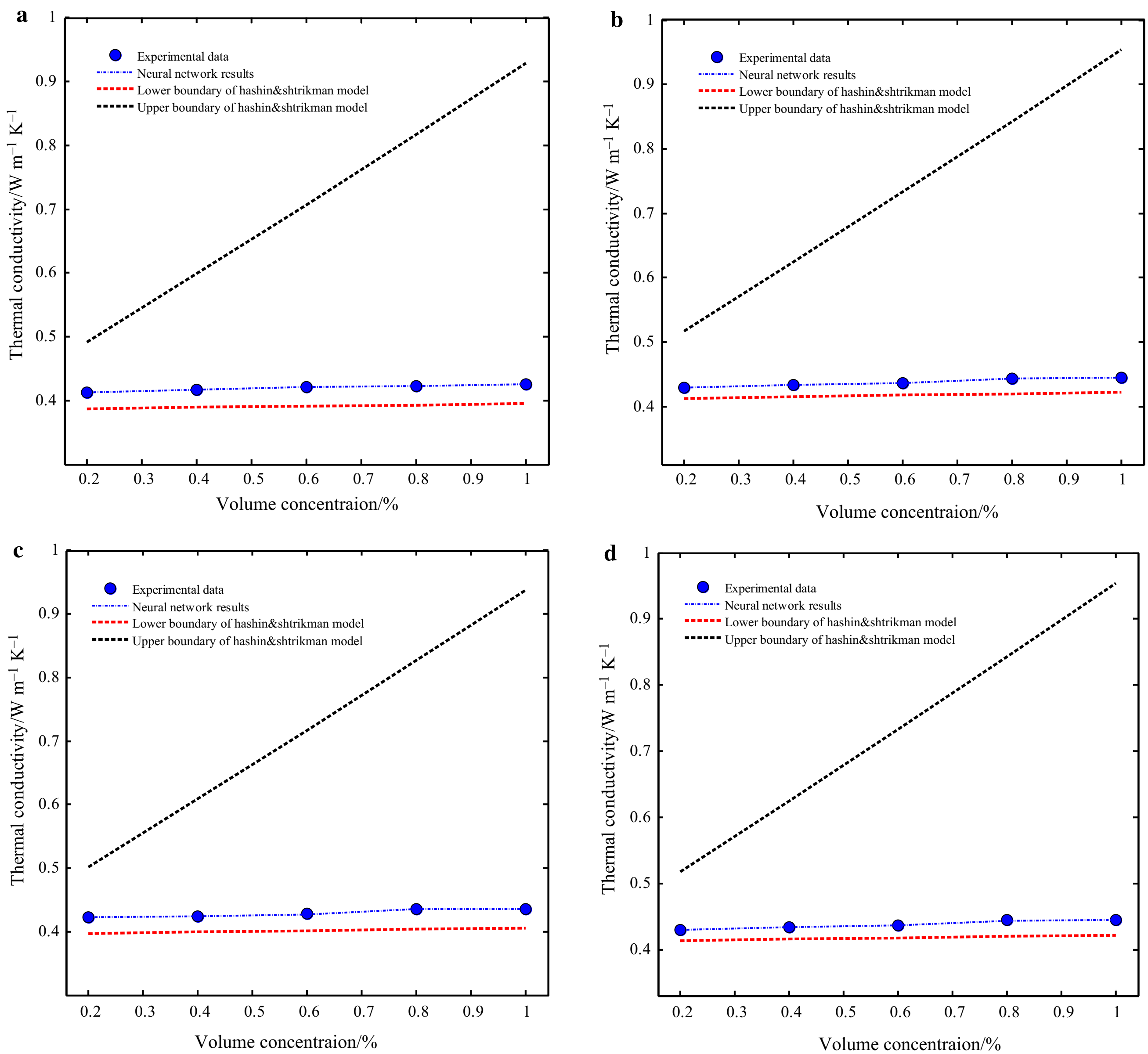

Fig. 7 Thermal conductivity versus volume concentration for a 30 °C, b 40 °C, c 50 °C, d 70 °C

seen, neural network can well estimate the experimental data with a high precision by training hidden layers (two hidden layers with five neurons in each layer) and adjusting the weights and biases. Figure 6 shows that the pattern selected for neural network modeling has been chosen well.

In this section, a comparison between experimental data and the theoretical model suggested by Hashin and Shtrikman [1] has been conducted. This model includes two boundaries: upper and lower. Its lower boundary has been equal to Hamilton–Crosser model. For its upper boundary, a relationship in terms of volume fraction and thermal conductivity of base fluid and nanoparticles has been suggested:

$$\frac{k_p + 2k_{bf} + 2\varphi(k_p - k_{bf})}{k_p + 2k_{bf} - \varphi(k_p - k_{bf})} \le \frac{k_{eff}}{k_{bf}} \le \frac{3k_{bf} + 2\varphi(k_p - k_{bf})k_p}{3k_p - \varphi(k_p - k_{bf})k_{bf}} \quad (1)$$

Figure 7a–d shows a comparison between experimental data, neural network modeling results, and upper and lower boundaries of Hashin and Shtrikman model.

From these figures, it is evident that experimental data are between upper and lower boundaries of Hashin and Shtrikman model. Neural network modeling can model and estimate the experimental data with a high precision.

These diagrams have been drawn for temperatures of 30, 40, 50, and 70 °C versus volume fraction.

Table 3 Regression parameters of the proposed correlation

S	R^2	R^2 (adj)	R^2 (pred)
0.0011853	98.51 %	98.01 %	97.48 %

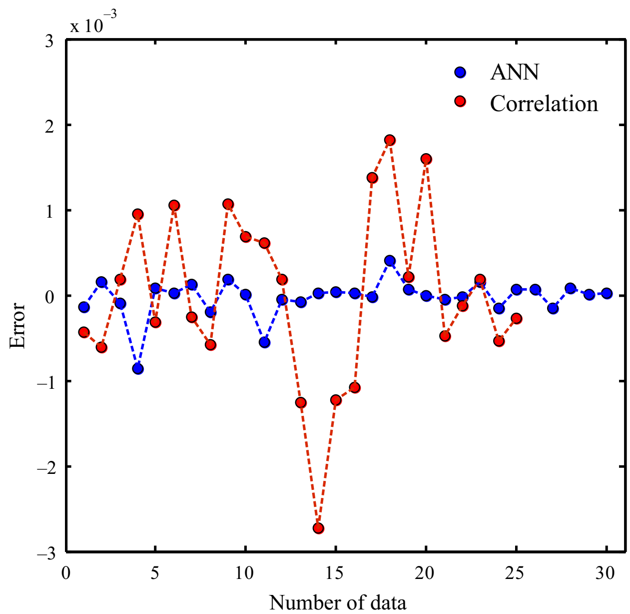

Fig. 8 Error of ANN and proposed outputs compared with experimental data

Presentation of the correlation based on experimental data.

In order to compare with neural network and also estimate thermal conductivity of nanofluids in terms of temperature and nanoparticles volume fraction, an experimental correlation has been presented based on experimental data.

$$k_{\mathrm{nf}} = 409 + 0.00053T + 412\varphi - 409\exp(\varphi) - 0.023T^{0.3} + \frac{0.000021}{\varphi} + 0.006T \cdot \sin(\varphi) \quad (2)$$

The regression parameters of this correlation have been presented in Table 3.

In order to have a better understanding of precision of MLP neural network and the suggested correlation and the value of their error, the value of error has been drawn (Fig. 8). The greatest value for neural network is $<10^{-3}$ and that of the correlation is $<3 \times 10^{-3}$, which shows the great power of neural network in modeling nanofluid thermal conductivity.

Conclusions

In this article, the experimental data of thermal conductivity of TiO_2–EG/water (50–50) were used. Then, post-processing operations were conducted on the data and the following results were obtained:

1. There are various artificial neural networks, each of which can be modeled from natural phenomena and predict the values that do not exist in experimental data.
2. The performance of all neural networks is not identical in simulation and modeling the data.
3. According to this research and the other researchers conducted, neural networks generally present a more precise estimation of nanofluids thermal conductivity compared to experimental correlation.
4. Neural networks are considered a very good tool for collecting experimental data and coming to a general conclusion regarding nanofluids.

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