A hybrid genetic–BP algorithm approach for thermal conductivity modeling of nanofluid containing silver nanoparticles coated with PVP

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Abstract

Since nanoparticles play a significant role in increasing the thermal conductivity of fluids, the present study aims to predict the thermal conductivity of silver nanofluid coated with polyvinylpyrrolidone (PVP) by the combinational model of multilayer perceptron artificial neural network and genetic algorithm. For modeling, the results of experimental measurements have been used for thermal conductivity of nanofluid containing PVP-coated silver nanoparticle-based deionized water at 25–55 °C in volume fraction of 250 ppm, 500 ppm and 1000 ppm. Henceforth, genetic algorithm is applied to improve learning process in the artificial neural network. It is in this way that the masses were chosen for each neuron's communications as well as their bias happens according to optimization performed by the genetic algorithm. To evaluate the accuracy of the model in predicting thermal conductivity of nanofluid, mean absolute percentage error, root mean square error, coefficient of determination (R^2) and mean bias error have exerted indices which are 1.202, 0.345, 0.989 and -0.016, respectively. The results of the indices and predictions, compared to the experimental results, show high accuracy and reliable combinational model of artificial neural network and genetic algorithm.

Keywords Thermal conductivity · Modeling · Artificial neural network · Genetic algorithm · Silver nanofluid

Introduction

Today, in consideration of an increment in costs of energy, the enhancement efficiency of energy-dependent systems in order that decrease their consumption is prominent [1]. Heat transfer is considered as one of the most significant processes causing energy consumption in the industry. Meanwhile, the thermal conductivity coefficient of fluids plays a salient role in the development of heat transfer fluids, and also, due to the increasing global competition, the preference for using fluid with higher thermal conductivity is inevitable for diverse industries [2]. The main limitation of heat transfer of common fluids that are being used in thermal systems such as water, oil and ethylene glycol is being intrinsic low thermal conductivity [3]. After more than a century since Maxwell's era, this issue leads researchers and scientists to improve the intrinsic low thermal conductivity of fluids by adding solid particles to them. With regard to the sedimentation and basic limitation in dispersion of particles with micrometer and millimeter sizes, the concept of nanofluid was introduced by Choi as a new topic in researches related to nano-based heat transferors. Nanofluids consist of a base fluid and suspended particles with a size of 1–100 nm [4]. Although thermal conductivity of nanofluids was measured with nanoparticles at first [5], nanofluids did not gain attractions until the time Eastman et al. [6] showed for the first time that copper nanofluids that are being prepared by a direct single-step volatilization method have higher thermal conductivity in comparison with nanofluids that are being prepared by a two-step method.

Metal's thermal conductivity is significantly higher than that of nonmetallic particles, and compared with the nonmetallic particles, the addition of metal particles to the base fluid increases the thermal conductivity more, leading to more acceptable results in the thermal absorbent systems [7,

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8]. In addition to the thermal conductivity of nanoparticles, including metal, nonmetallic and polymer [10] in different application such as nanocomposite [11, 12] and nanoporous [13, 14], there are certain properties too such as absorption, diffusion and color, which makes the use of nanoparticles more prominent in thermal systems [14–19].

Pourrajab et al. [20] have shown that thermal conductivity of the hybrid nanofluid (0.04 vol% Ag plus 0.16 vol% MWC-NTs) and base water improved by 47.3% in comparison with base fluid. In other research of them, the results of their study showed that by increasing concentration and temperature of the nanocomposite the ratio of thermal conductivity of hybrid nanofluids based on mesoporous silica modified with copper nanoparticles nanofluids was enhanced [21].

Experimental methods lead to valid, accurate and credible results in all scientific fields of studies when using standardized equipment and carrying out comprehensive studies. Due to the fact that empirical methods require special equipment and facilities and this increases the costs and time needed to perform experiments, it is permissible to use modeling methods and algorithms as replacements [22–24]. Nowadays, among different modeling methods, an artificial neural network is considered as one of the important methods in artificial intelligence which is influenced by human brain ability to identify phenomena. Artificial neural network modeling is known as a powerful tool in various advanced scientific and engineering topics to solve complicated problems. Regarding its high running speed, widespread capacity and also simplicity of applying ANNs in comparison with classic methods, numerous scientists tend to use this modeling method to predict thermophysical [25–29], viscosity [30–32] and thermal conductivity [33–36] properties of nanofluids.

Hemmat Esfe et al. indicated that artificial neural networks provide more reliable results than those of theoretical relationships in their research on diverse nanofluids thermal conductivity modeling such as Cu/TiO$_2$–water/EG hybrid [37], Al$_2$O$_3$–water [38], ZnO–MWCNT/EG–water [39], SWCNT–MgO hybrid [40], SiO$_2$–MWCNT [41], SWCNT–ZnO [42] and MWCNTs–ZnO/5W50 [43].

The thermal conductivity of nanofluid containing graphene nanoplates and deionized water is investigated by Khosrojerdi et al. [44]. They calculate the root mean square error (RMS error), detection coefficient and mean absolute percentage error (MAPE) to determine the accuracy of their model which are 0.04 W m^{-1} K^{-1}, 99% and 0.26%, respectively.

With the experimental analysis of the nanofluid thermal conductivity attributes of graphene oxide, Tahani et al. [45] predicted and modeled their experimental results using artificial neural networks. Their results show that the neural network with two inputs (volume fraction and nanofluid temperature) and one output parameter (nanofluid thermal conductivity) together with two hidden layers and one visible layer of Tansig, Logsig and Purline functions with 4-8-1 neuron numbers has the best modeling structure.

In research on nanofluid thermal conductivity modeling, such as MgO–MWCNTs/EG hybrid, Vafaei et al. [46] showed that the 12-neuron neural network in its secret layer has the best results compared to experimental results. The largest discrepancy between modeling results and experimental results was 0.8%. Afrand et al. [47] investigated the effect of neuron numbers in the neural network layers, with respect to temperature parameter and nanofluid volume percentage of MgO–water, and their research showed that the number of seven neurons has the least error compared to the experimental results.

Vakili et al. [48] modeled the thermal conductivity of copper oxide using FFBP–ANN method, and their results showed that the neural network with two hidden layers and number of four and ten neurons has better results than those of theoretical methods.

Kavitha et al. [49] showed in their research that the MLP model compared to the SVR model has the better results in estimating the thermal conductivity of nanofluids. MLP model requires more experimental data than the SVR model. Therefore, they proposed SVR model when experimental data are limited.

Ahmadi et al. [50] modeled the viscosity of a water-based Fe$_2$O$_3$ nanofluid, and their results showed that the model has 0.9962 and 0.9982 amounts in the R-requested index.

Alrashed et al. [51] showed in their research on the carbon-dependent thermophysical properties of nanofluids that the nanoparticle volume percentage, temperature and the type of materials have a direct effect on modeling accuracy.

Agarwal et al. [52] investigated the performance of nanofluids containing Fe$_2$O$_3$ for the use in heat transfer systems. The performance of nanofluids was investigated in terms of the effect on the thermal conductivity by increasing the concentration of Fe$_2$O$_3$ nanoparticles in water-based liquids and ethylene glycol at 10, 20, 30, 40, 50, 60 and 70 °C. The results of their study showed that the outcome of ANN modeling is in good agreement with the experimental results and H-C model offers better predictions than other standard models.

Another optimization topic that can be applied in modeling is genetic algorithm. The genetic algorithm inspired by nature and Darwin's evolution theory is based on the survival of the fittest or natural selection. Regarding the features of genetic algorithm compared to other optimization method, it can be said that it is an algorithm which can be applied for any problem without any knowledge of it and there is no restriction on the type of its variables, and it has a proven ability to find the global optimum [53].

Karimi et al. [54] predicted the density of four nanofluids at 323–273 K, using artificial neural network of

back-propagation and genetic algorithms. Their modeling results show the proper accuracy with absolute deviation of 0.13% and high correlation coefficient of $R \geq 0.98$. Karimi et al. [55] also in another study predicted the nanofluids viscosity properties, using artificial neural network and genetic algorithms. In this study, they modeled using the experimental results of eight nanofluids, which showed that there is a good balance between the predicted amounts by the model and experimental results. The amount of absolute deviation is 2.48% and correlation coefficient is 0.98.

Ramezanizadeh et al. [56] predicted thermophysical properties of nanofluid containing Al_2O_3/water using different modeling methods such as GA–LSSVM, PSO–LSSVM, HGAPSO–LSSVM and ICA–LSSVM, and their investigation results showed that GA–LSSVM model, which is the combination of genetic algorithm and least-square support vector machine, yielded a more acceptable result than the other methods.

A study conducted by Ahmadi et al. [57] on the thermal conductivity properties of Al_2O_3/EG nanofluid using GA–LSSVM showed that the use of genetic algorithm in this type of modeling caused the accuracy of model to be 0.9902 in terms of R^2 coefficient, indicating the high accuracy of the designed model. They also showed in their research on Fe_2O_3/water nanofluid that the combination of radial basis function neural networks with genetic algorithm yields better results than other models [50]. Hemmat et al. [58] applied a combination of neural network modeling and genetic algorithm to model the viscosity and thermal conductivity of Al_2O_3–water/EG (20–80), and the results of their comparison with the experimental results showed that modeling with this method is very accurate.

Amani et al. [59] investigated the performance of artificial neural networks and genetic algorithms in modeling the viscosity and thermal conductivity of nanofluids containing $MnFe_2O_4$. According to the results of their research, the use of the genetic algorithm in neural network modeling can help to increase model accuracy. In their other research, they investigated the application of ANN, empirical correlations and genetic algorithm in modeling the thermophysical properties such as thermal conductivity of nanofluid including C-MWCNT/water. Their results showed the use of artificial neural network with algorithm genetic compared to empirical correlations obtained from nonlinear regression method is better [60].

With studies conducted on the role and performance of artificial neural network and the use of genetic algorithm in modeling of nanofluid's thermophysical properties, in this study with the use of combination of perceptron multilayer artificial neural network and genetic algorithm, it will be dealt with modeling and predicting thermal conductivity of nanofluid containing silver particles with

Table 1 Properties of nanoparticles

Attributes	Properties
Appearance	Black
Purity	99.99%
APS	20 nm
SSA	18–22 $m^2\,g^{-1}$
True density	10.5 $g\,cm^{-3}$
Morphology	Spherical

Fig. 1 A picture of the sample and Hielscher Ultrasonic UP400S

water-based polyvinyl pyramid coating at volume fraction and different temperatures.

Experimental

Materials and methods of nanofluid preparation

In this study, silver nanoparticle with polyvinyl pyramid coating (US Research Nanomaterials, Inc., USA) was used as the particle of nanofluid factor based on deionized water. The properties of the nanoparticle are listed in Table 1.

In this study, a two-step process was used to prepare nanofluid due to different processes of nanofluid preparation. In this method, the nanoparticles were scattered with volume fractions of 250 ppm, 500 ppm and 1000 ppm in the fluid, that is, deionized water. In order to propagate nanoparticles in the base fluid, an ultrasonicator with power of 400 W (Hielscher Ultrasonic UP400S, Teltow, Germany) was used, which is depicted in Fig. 1.
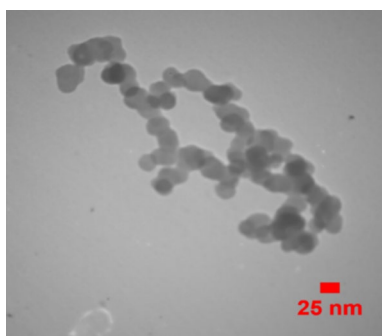
Method of investigating the properties

Due to the nature of nanofluid which is a mixture of nano-particles and base fluid, the thermophysical properties of a nanofluid are a function of its constituent's properties. Therefore, accurate understanding of nanoparticles properties is necessary. So in this study, nanoparticles and their structure were analyzed by the two methods of transmission electron microscopy, TEM, and X-ray diffraction. In this method, the transmission electron microscope of model TEM, EM900, Zeiss, Germany, with an acceleration voltage of 80 kV was used. Figure 2 displays TEM photograph of silver nanoparticle coated with PVP.
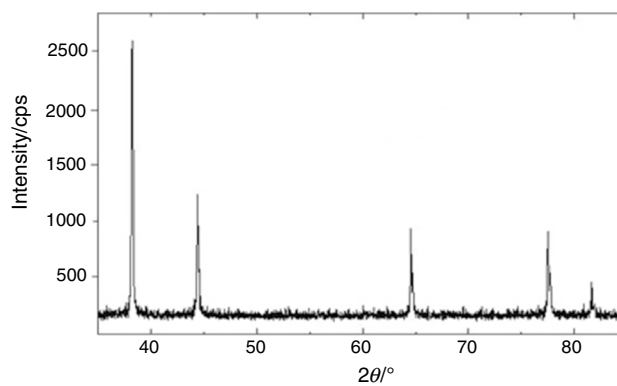
To investigate the crystalline structure of nanoparticles, EQUINOX 3000, Inel Inc., Artenay, France, was used, which has a measuring range of 5°–120°. The results of the measurements are shown in Fig. 3. According to X-ray diffraction of silver nanoparticle, a reflection in the XRD pattern of silver nanoparticles at 2-h values of 38.28, 44.45, 64.25 and 77.52 degrees attributed to the 111, 200, 220 and 311 planes of Ag, respectively, showed the structure of crystalline was cubic. The peaks in Fig. 3 show that the main composition of nanoparticles was Ag and no peaks of an impurity phase were found in the XRD patterns.

The dispersion quality of nanoparticles inside the base fluid is one of the important things in studying the thermophysical properties of nanofluids [61]. The clogging and sedimentation phenomena in nanofluids reduce their effects and properties as operating fluid, and it can even prevent them from being used in thermal systems as deterrent. Therefore, it is important to investigate the stability amount of nanofluids. To evaluate the stability and dispersion amount of nanofluids, there are several methods. In this method, the stability has been studied by a Zetasizer, ZEN 3600, Malvern Instruments Ltd., UK, for measuring the zeta potential and particles size.

The results of nanoparticles diameter determination of the nanofluid sample of 1000 ppm are shown in Fig. 4. According to these results, nanoparticles size obtained is equal to


**Fig. 3** The results of X-ray diffraction of silver nanoparticle

82.38 nm. In general, the zeta potential amount introduced as the stability boundary, in terms of the evaluation of nanofluid zeta potential amount, is 25 mV (positive or negative) [62] so that nanofluids with zeta potential of more than $+30$ and less than -30 have a good stability [7]. In this study, according to the measurements, nanofluids which have been made from silver have a zeta potential of -41.6, indicating that nanofluids have good stability. The measurement results are shown in Fig. 5.

By applying the simultaneous thermal method (Shimadzu, DTG-60), TGA and DTA spectra were carried out in the temperature range from room temperature to 700 °C. The corollary of the test is reported in the figure. According to the TGA curve, the mass loss of sample between 100 and 300 °C is higher than other temperatures, noticeably. To the extent that, the negligible amount of mass loss can be observed in other temperatures. Also, based on the DTA curve, due to crystallization of silver nanoparticles, an extreme exothermic peak is occurred between 200 °C and 300 °C which is coincided with complete thermal decomposition (Fig. 6).

Thermal conductivity coefficient plays a key role in improving the effect of thermal transferring nanofluids with

Fig. 2 The picture TEM of silver nanoparticle with PVP coating
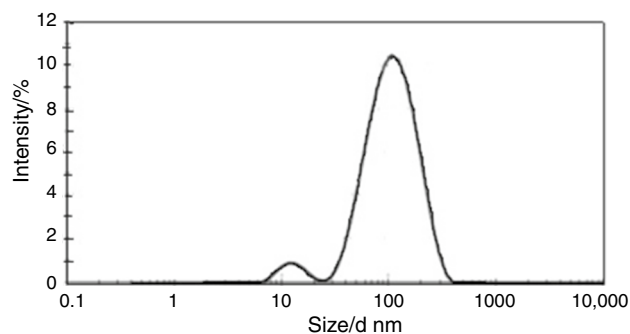
Fig. 4 Results of dispersed nanoparticles size measurement in nanofluids with volume fraction of 1000 ppm
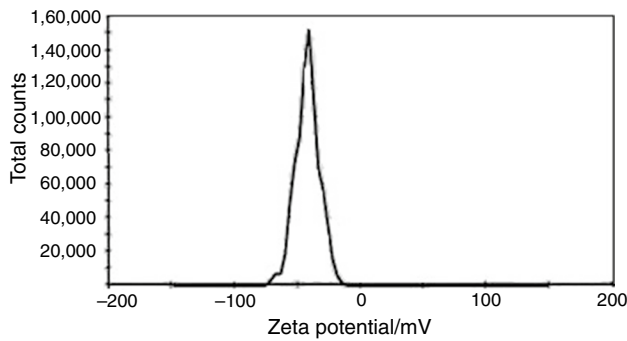
Fig. 5 The results of nanofluid Zeta potential measurement with volume fraction of 1000 ppm

Table 2 Density of nanofluids

Sample	Concentration/ppm	Density/g cm^{-3}
DI water	Zero	998.2
Ag1	250	1000.75
Ag2	500	1002.51
Ag3	1000	1007.02

energy efficiency. The effective thermal conductivity coefficient of nanofluids is typically measured by the transient hot wire method. In the transient hot wire method, a thin metal wire is used as the linear thermal source and the temperature sensor. This wire is surrounded by a nanofluid whose thermal conductivity coefficient must be measured. Then, this wire is heated by passing current through it. Now, the higher the thermal conductivity coefficient, the lower the wire temperature. This principle is used to measure the thermal conductivity coefficient.

The density of the prepared nanofluid shown in Table 2 was calculated by Pak and Cho equation [63] (Eq. 1), in which φ is the volume concentration and ρ_f and ρ_p are the density of base fluid and nanoparticle, respectively.

$$\rho_{nf} = (1 - \varphi)\rho_f + \varphi\rho_p. \tag{1}$$

As it can be found that due to the low concentration of nanofluids, the density of nanofluids does not have a noticeable deviation from density of DI water.

In this study, the transient hot wire method was used for measuring the thermal conductivity coefficient of nanofluids at a temperature range of 25–55 °C by KD2 Pro, Decagon

Devices Inc., USA. According to the specific information of KD2, the accuracy of the determined thermal conductivity is $\pm 5\%$ for the range of 0.2–2 W m^{-1} K^{-1}. In this experiment, three measurements were performed separately and with a time interval of 15 min for every nanofluid sample, finally their numerical mean has been calculated and reported as the thermal conductivity of the sample.
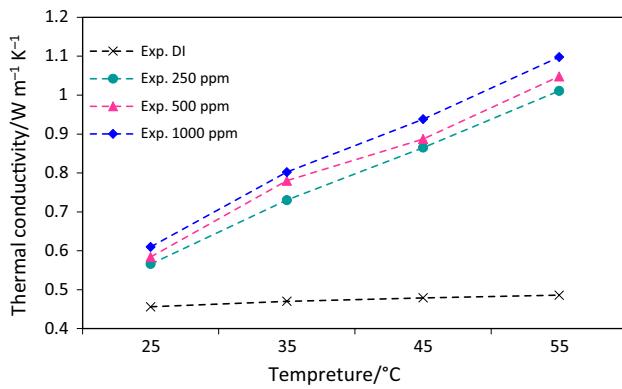
The measurement of thermal conductivity

Nanoparticles increase the heat transfer speed in the nanofluid by increasing the nanofluid thermal conductivity and generating heat propagation in the current. Since nanoparticles have much more contact surface area than micro- and other larger particles, and also increasing the contact surface causes an increase in the effective surface of heat transfer, in this section we consider the importance of increasing the nanofluid volume fraction compared with increasing the temperature than increasing the thermal conductivity coefficient. The silver nanofluid was measured at temperatures of 25–55 °C in different volume fractions, and the results of the empirical measurement are shown in Fig. 7.

As shown in Fig. 7, the nanofluid thermal conductivity is highly dependent on temperature, so that as the nanofluid temperature increases, its thermal conductivity rises too. Much movement and mobility of nanoparticles with increasing temperature due to the Brownian motion phenomenon is one of the reasons of this dependence on temperature. It is in this way that as the temperature increases, the base

Fig. 6 The DTA–TGA curve of silver nanoparticles
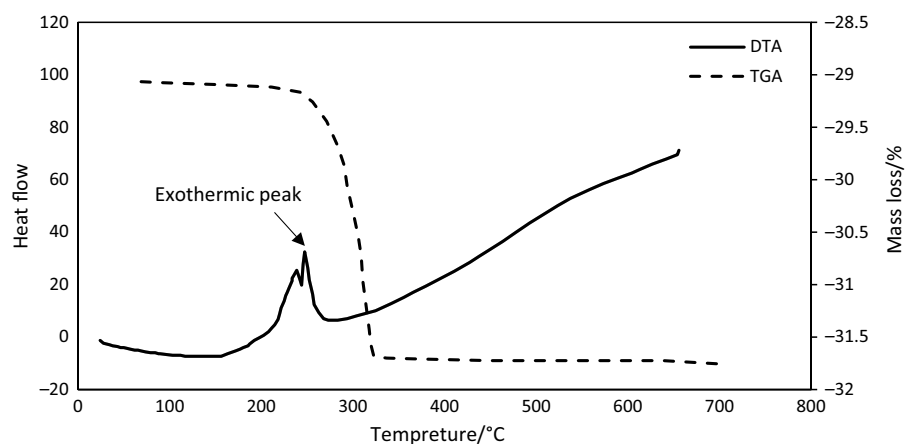
Fig. 7 The amount of thermal conductivity of sample nanofluids and deionized water at different temperatures

fluid viscosity decreases and the scrambling or Brownian motion of the nanoparticles escalates. Also, according to the results, by increment in temperature, thermal conductivity of DI water increases slightly, because there is no particle in DI water and the rise of temperature does not have a tangible impact on thermal conductivity.

Silver has some special properties. Among all metals, silver has the highest amount of thermal conductivity being 700 times more than water. In addition, silver is non-toxic and has well compatibility with environment which lead it to be one of the most significant metals in nanotechnology. Also, according to researches, silver nanofluid has an acceptable range of stability. Meanwhile, applying

polyvinylpyrrolidone (PVP) as surfactant leads to improving silver nanofluids stability.

Hybrid modeling

Artificial neural networks are one of the advanced and modern methods in simulation and modeling which are used today in all branches of different sciences as a powerful tool in simulating those phenomena whose conceptual analysis is difficult. In this method, the observational data are trained to the model, and after training, the model performs prediction and simulation work with proper accuracy. In general mode, an artificial network acts as a function and receives input variable for the quantity of input-layer neurons and output variable for the quantity of external-layer neurons.

In this study, the input parameters include temperature and volume fraction of nanofluid that are placed in the first layer. Due to the masses belonging to neurons and also the number of different neurons in the middle, at the end and in the final layer, the thermal conductivity of nanofluid has been considered as the output of the network. In Fig. 8, performance structure of the neural network is shown.

Neural networks with their remarkable ability to derive meaning from complicated or ambiguous data can be used for extracting patterns and identifying methods that their understanding is very complex and difficult for human and other computer techniques. The important assumptions in the artificial neural network are as follows:

Fig. 8 Schematic picture of ANN structure to predict the thermal conductivity of silver nanofluid at different temperatures
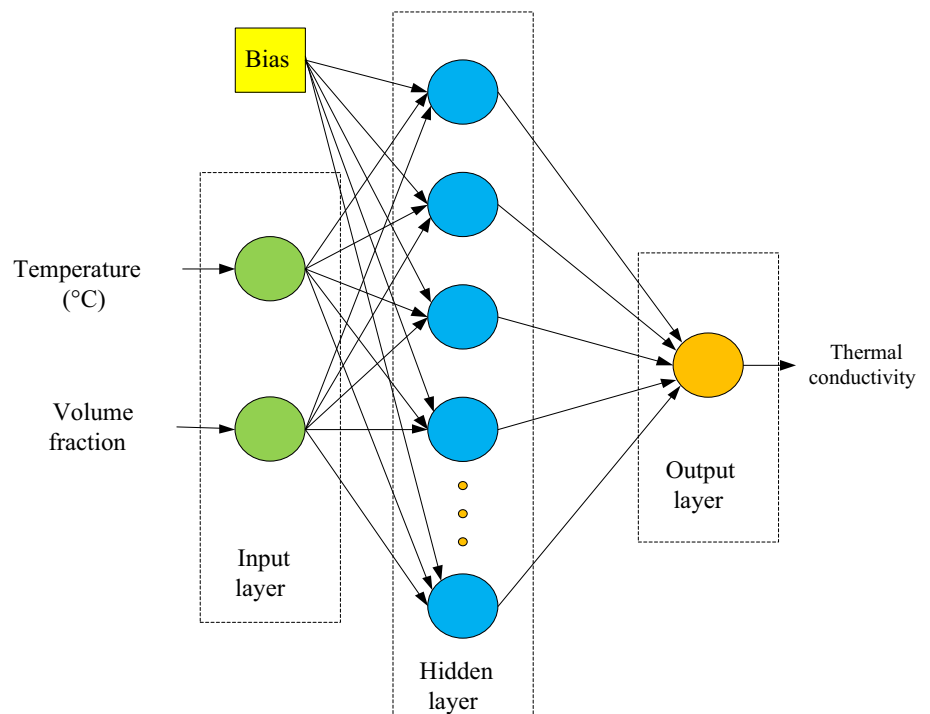
1. Data processing is done in the simple components called neurons.
2. The information between neurons is transmitted through their communication.
3. Each of these relationships has their own mass which multiplies by the amount of exchanged information with other neurons, and these masses are adjusted over time. In fact, it is from this perspective that the network is educated and influenced by the environment. Each neuron has an operating function for its output calculation, which is usually a nonlinear function and applies to inputs. The artificial neural network learns to solve a problem and is not actually planned ahead. In fact, the input masses adjusting of each neuron causes the learning of the whole network, which can be done with or without an observer based on the implemented model. Artificial neural network can have multiple layers or one layer. Modeling with nonlinear systems, resistance and damage tolerance, learnability means the ability to adjust the network masses, generalizability, high speed due to parallel processing, adaptability to system changes and so on which are features of the artificial neural network.

The genetic algorithm is inspired by genetic science and Darwin's evolution theory and is based on the survival of the best or natural selection. A common application of genetic algorithm is using it as an optimizer function. Genetic algorithm is a useful tool in the pattern recognition, feature selection, image understanding and machine learning [64, 65]. In genetic algorithms, the genetic evolution manner of the living creatures is simulated.

In a genetic algorithm, a population of people will survive in the environment according to their desirability. People with superior abilities will find better chance of marriage and more reproduction. So after a few generations, children with better performance are born. In the genetic algorithm, each individual from population is introduced as a chromosome, and the chromosomes become more complete over several generations. In each generation, chromosomes are evaluated and have the survival and reproducible ability according to their value, and superior parents are chosen on the basis of a fitness function [66].

The genetic algorithm generates a new generation by considering a set of answer space points in each computational iteration, or by performing genetic operators on them, and drives it over the optimal cycle. The benefits of the genetic algorithm method are: In the process of searching, it only needs to determine the value of the target function at different locations and does not use any additional information such as the derivative of the target function. Therefore, it can be used in a variety of problems, including linear, nonlinear, continuous and discrete, and can easily be adapted to

a variety of issues including thermal conductivity prediction of nanofluids.

At each stage of the genetic algorithm implementation, a group of search space points are randomly processed. It is in this way that a sequence of characters is assigned to each point and genetic functions are applied to these sequences. The resulting sequences are then decoded to obtain new points in the searching space. Finally, depending on how much the objective function is at each of these points, their likelihood of participating in the next step is determined. Figure 9 shows the structure combination of artificial neural network and genetic algorithm.

In the present study, genetic algorithm has been used to improve learning process in the artificial neural network. It is in this way that the masses are chosen for each neuron's communication and also their bias amount is based on the optimization performed by the genetic algorithm. After assigning the amount of masses and tendency of each layer with the help of genetic algorithm, the network is going to train itself and finally presents its proposed model according to the considered error.

The modeling training section begins with the genetic algorithm in accordance with the steps outlined as follows:

1. At first, the population is selected randomly. The characteristics of each individual in the first generation are selected randomly from the mass amount in the artificial neural network.
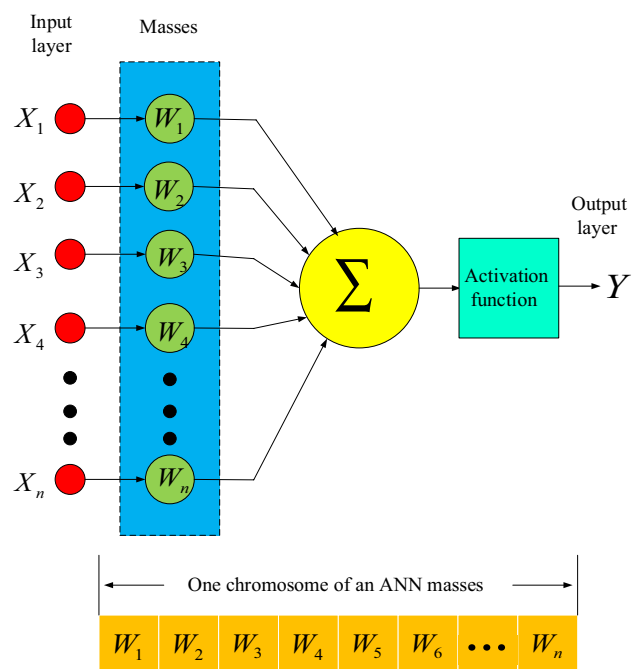

Fig. 9 The combination structure of neural network and genetic algorithm

2. Each individual from population is examined. To do this, the neural network is run according to the determined inputs and output and on the basis of determined masses for every neuron and layer, and finally, the modeled output is compared with the experimental amount.
3. The population are ranked in terms of the least error of neural network.
4. The best person of the population with the least error will be moved to the next generation (elitism).
5. Using the genetic algorithm operators, the best parents are selected for reproduction.
6. This procedure is repeated for the second generation, and the algorithm is run for a defined number of cycles. The final set of each neuron's masses (the chromosome which is selected from the best person in the past generation) is selected for neural network training.
7. After finishing the genetic algorithm training, the neural network algorithm begins to solve.

Figure 10 shows the flowchart of computational and modeling of nanofluid viscosity prediction on the basis of nanoparticles volume fraction and its temperature.

In the present study, with the use of MATLAB R2019a software and considering an initial population of 150, the number of generations equals 50 and the cross-linking rate is 0.5 and the mutation rate is 0.2 of the happened modeling. The stopping condition of algorithm is the failure of the target function to progress for 50 consecutive generations or finishing the number of generations. In order to replace the newborn children with the population of past generation, it is in this way that from the parent population and the children population, those chromosomes that have more elegance have been selected as the alternative population.

Statistical analysis

In this study, statistical measures of root mean square error (RMSE), average absolute percentage of error, coefficient of determination and mean deviation error have been used to evaluate the accuracy and the performance of model and network. The measures of RMSE, average absolute percentage of error and mean deviation error are good indicators for determining the accuracy of the model, so the closer these two indices are to zero, the higher the model accuracy. The coefficient of determination indicates the probability of correlation between two datasets in the future, and when this number is closer to zero, it shows the better performance of the model [67]. The relationships used for calculating of the above indices are described as follows:
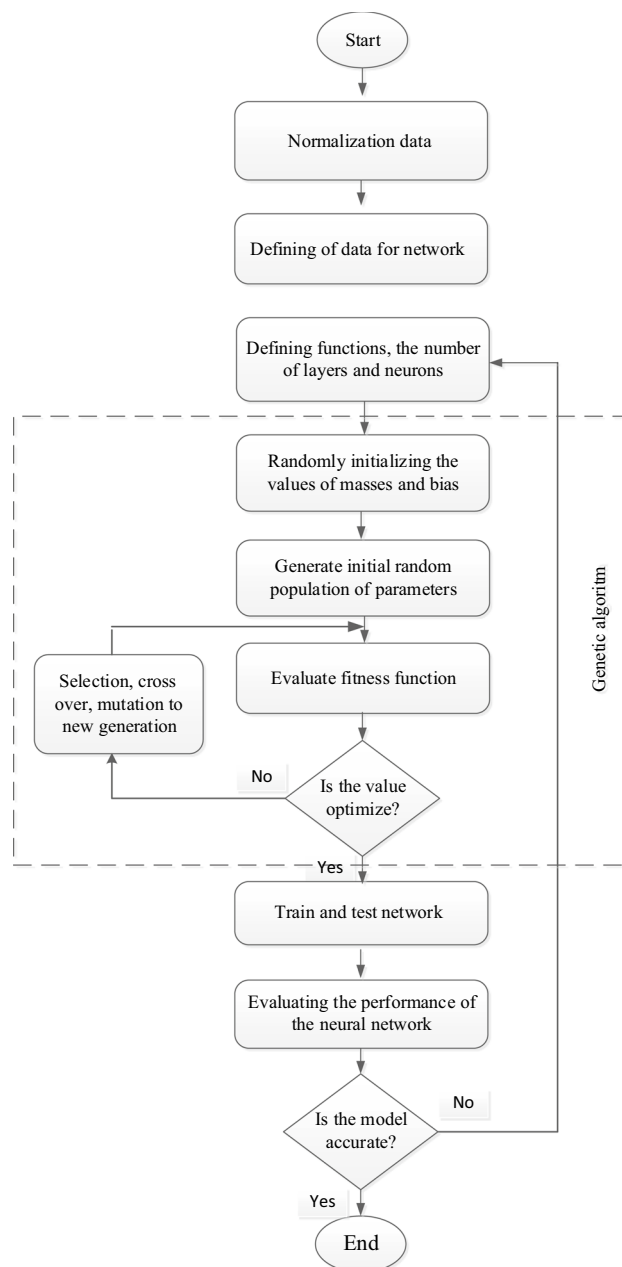
Fig. 10 The modeling computational flowchart with the help of artificial neural network and genetic algorithm

$$\text{RSME} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (k_p - k_a)^2} \tag{2}$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{(k_p - k_a)}{k_a} \right| \times 100 \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (k_a - k_p)^2}{\sum_{i=1}^n (k_a - \bar{k}_a)^2} \qquad (4)$$

$$MBE = \frac{1}{n} \sum_{i=1}^n (k_p - k_a) \qquad (5)$$

where k_p is the predicted thermal conductivity and k_a is the real thermal conductivity. $\bar{k}_a$ is the average of real thermal conductivity over the measured period and n is the number of measured samples.

Results

According to flowchart shown in Fig. 10, the modeling has been performed with the help of artificial neural network and genetic algorithm. At this stage using the trial-and-error method, the number of neurons, layers and network functions has been modified in each modeling, and the results of the model accuracy and validity as well as statistical indices have been recorded, which are shown in Table 3.

According to the performed optimization by the genetic algorithm during the modeling training phase to determine the mass of layers and the desire amount of each of them, the optimization result under different conditions such as the number of neurons and activation functions is shown in Fig. 11. In order to study and select of the most optimal model for network training, the mean square error (MSE) has been used.

Since the elitism occurs in the optimization process of each generation change, the shown error rate is reduced after several repetition and the most optimal solution is selected. This trend continues until the model design is defined that the number of 50 generations has been selected in this study. As shown in Fig. 11, this amount is of desirable value, since no significant change has been observed in the error rate after repeating the generations. Therefore, this number has been considered as the desirable amount to reduce the modeling and computational time. According to the results
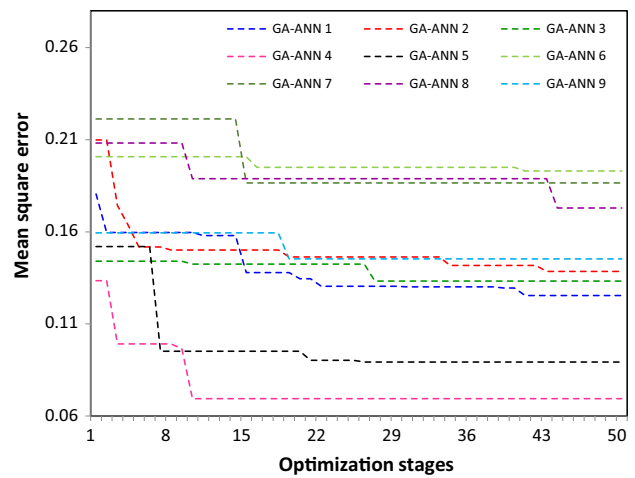

Fig. 11 Mean square error of each optimization stages based on the number of neurons and different functions

shown in Fig. 11, the Tansig function on average has a better performance for optimization selecting of the layer's masses and has the least mean square error in the training step by genetic algorithm in 50 generations.

For better investigating of the functions role on optimization amount by genetic algorithm, Fig. 12 shows MSE index for each model. In this index, the closer the number is to zero, the model shows more proper function. With respect to averaging from the obtained results of MSE index for both two defined functions, it can be concluded that Tansig function with a mean of 0.111 in the created models has a better performance than Logsig function with a mean of 0.174. As shown in Fig. 12, the selection of neurons' numbers does not follow a specific trend and only through their random selection the desired result can be achieved.

In order to select the proper model among the applied modeling, statistical indices of each model will be considered. Since the number of the middle layers neurons is randomly selected, it is important to investigate the statistical indices as one of the proper methods for selecting the appropriate model among the existing methods. So, the results of

Table 3 The results of model accuracy measurement indices according to different conditions

Model	Function	Neurons	MBE	R^2	RMSE	MAPE
GA–ANN 1	Tansig–Purline	3-1	− 0.011	0.973	0.374	4.42
GA–ANN 2	Tansig–Purline	6-1	− 0.016	0.989	0.345	1.202
GA–ANN 3	Tansig–Purline	10-1	− 0.055	0.985	0.38	5.42
GA–ANN 4	Tansig–Purline	14-1	− 0.052	0.973	0.355	8.96
GA–ANN 5	Tansig–Purline	19-1	− 0.135	0.969	0.293	6.3
GA–ANN 6	Logsig–Purline	5-1	0.075	0.57	0.419	24.14
GA–ANN 7	Logsig–Purline	9-1	0.04	0.529	0.429	49.41
GA–ANN 8	Logsig–Purline	12-1	0.045	0.922	0.4	23.52
GA–ANN 9	Logsig–Purline	17-1	0.029	0.91	0.374	8.99
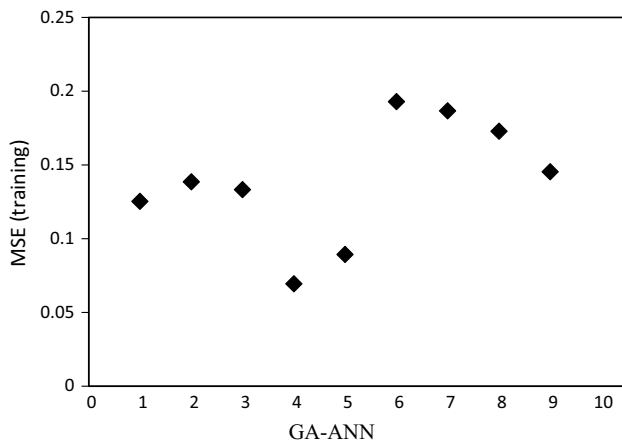
Fig. 12 The result of computing MSE index for each model

each index for each model are shown in Fig. 13. According to the results of part a, MAPE index for Tansig function with different neurons numbers was below 9% and for Logsig function was below 50%. Since in this criterion, the closer this index to zero, the better performance you can see, the GA–ANN 2 with 1.20 is the best model among the created models. The RMSE index, like MAPE index, is closer to zero, indicating the accuracy and correctness of the created model. By investigating and observing part b, it can be concluded that GA–ANN 2 with 0.345 has better accuracy than other models. With analyzing by R^2 index that its results have been shown in part c, based on the performance of the accuracy and correctness of created models, it can be concluded that GA–ANN 2 model with 0.989 has the best performance. In this criterion, the closer the index to number 1, the model will be in the more appropriate mode and the predicted results of that will have a better reliability. The final index that was evaluated for examining the performance of prediction models of silver nanofluid thermal conductivity has been the MBE index; in this measurement criterion, the closer this number to zero, the index will be in the better condition. As shown in section d, the numbers have been recorded between the positive and negative intervals. In this index, the sign of numbers, negative or positive, does not indicate the accuracy and correctness of the model, but they show just the model deviation from the real value. This means that the negative sign shows the model's tendency to predict less than the real value and the positive sign shows the model's tendency to predict more than real value. With created investigation on the results obtained from this index, the GA–ANN 2 model with -0.016 has the better accuracy among other models and tends to be resulted in prediction of less than real value. Finally, by investigating all parameters and statistical indices, it can be concluded that GA–ANN 2 model with six neurons in the middle layer and one neuron in the final layer is the most appropriate model.
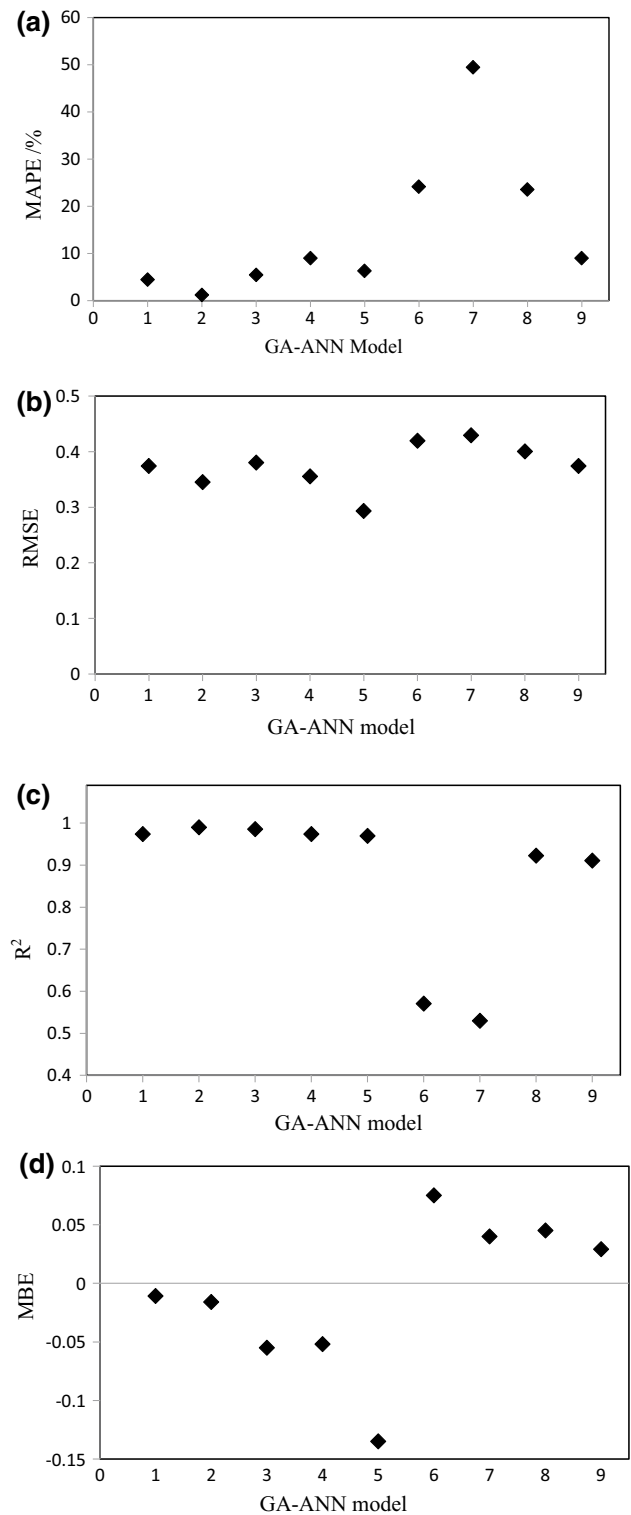
Fig. 13 The investigation results of models statistical indices **a** MAPE index, **b** RMSE index, **c** R^2 index, **d** MBE index

In general, the accuracy and correctness are evaluated for all modeling methods. A model has desirable validity when, in addition to the low error of its estimation in predicting

the sample data, it has sufficient precision to make out-of-sample predictions and its predictions have somehow been generalizable.

It is also no exception for the artificial neural network which has been used as a method of estimation in this study. When the neural network provides close and acceptable estimates for the sample data, but performs poorly for non-sample data, in fact it has lost his validity and over-fitting has been done like a complication.

After investigating the performance of the network system in the training section by genetic algorithm, ensuring the proper performance of modeling, finally for the use of obtained information, the extracted results from the network should become out of normalization mode. The predicted amount of silver nanofluid thermal conductivity with PVP coating in the volume fraction of 250 ppm, 500 ppm and 1000 ppm and in the temperature range of 25–55 °C is shown in Fig. 14 compared to the measured experimental results.

The results of combined set obtained from the modeling in Fig. 14 show that the predicted and experimental data in general mode have notable overlap to one another. In order to better evaluate the performance of the neural network and to see the difference amount between the predicted values of the nanofluid thermal conductivity with different volume fractions at temperatures of 25–55 °C in Fig. 15, the obtained results of modeling and predicted amounts of neural network along with the measured values have been shown experimentally. As shown in Fig. 15, the least amount of difference between the measured and predicted results is at 45 °C temperature.

In Fig. 16, the correlation of the obtained results from predicting the optimal model and the experimental measurement amount of silver nanofluid thermal conductivity is
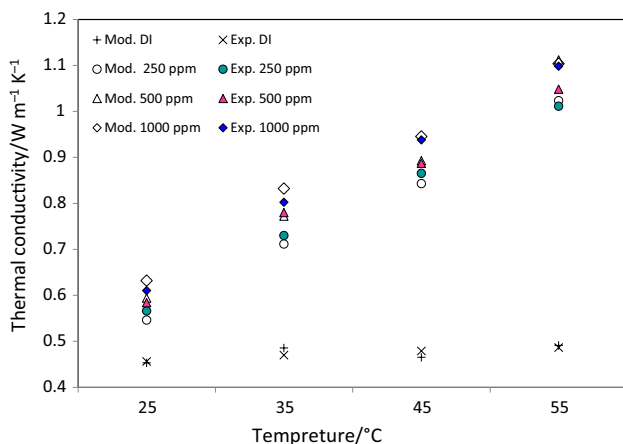

Fig. 15 Comparison of predictive and experimental amounts of silver nanofluid thermal conductivity at different temperatures and volume fractions
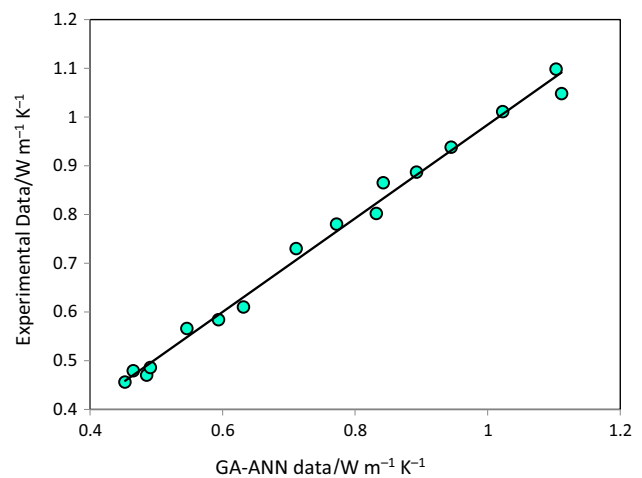
Fig. 16 Graph of correlation between measurement results and combinational model of artificial neural network and genetic algorithm

shown. According to the chart, more data are on or near the bisector, indicating that there is a proper relation between the experimental and output data of predicting. According to the performed study and obtained relation, there is a good correlation between the predicted and experimental amounts and data have a linear relationship and are of the first order.

Conclusions

Due to the importance of investigating and measuring the thermophysical properties of nanofluids, in this study we investigated and used from combined function of genetic algorithm and artificial neural network of perceptron multilayer to predict the silver nanofluid thermal conductivity with PVP coating on deionized water. The nanofluid thermal

Fig. 14 Comparison of experimental results of silver nanofluid thermal conductivity and the prediction amount of combination model of artificial neural network/genetic algorithm
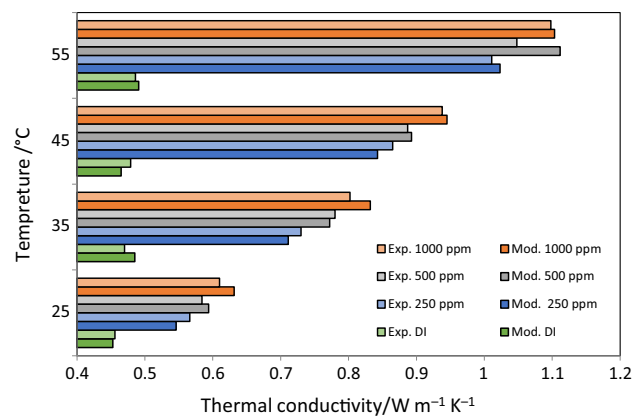
conductivity with different volume fractions was experimentally measured at temperature range of 25–55 °C. Since the nanofluid has a strong dependence on temperature, according to the experimental results obtained, increasing the temperature causes the increasing silver nanofluid thermal conductivity based on deionized water. Also, in the performed studies, increasing the nanofluid volume fraction causes the increase in thermal conductivity at each measured temperature. Experimental measuring results have been used for modeling with the help of combining the artificial neural network and genetic algorithm. Modeling was performed under different conditions such as the number of different neurons and different activation functions, that after selecting the optimal model, the amounts of predicted thermal conductivity were compared with its experimental amounts, and the obtained results of the model show the combination reliable accuracy of the artificial neural network/genetic algorithm compared to the obtained amounts from experimental measurements. The results show that using a hybrid artificial neural network and genetic algorithm model to predict the thermal conductivity of different nanofluids yields more accurate results than other modeling methods developed by other researchers.

Since laboratory operations and experimental measurements require special facilities and equipment and are usually costly, the use of combinational model of genetic algorithm and artificial neural network presented in this study is suggested for measuring the silver nanofluid thermal conductivity with PVP coating.

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