Thermal conductivity estimation of nanofluids with TiO_2 nanoparticles by employing artificial neural networks

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Abstract

Applying nanofluids in energy-related technologies and thermal mediums can lead to remarkable enhancement in their efficiency and performance due to their modified thermophysical properties. Among thermophysical properties, thermal conductivity (TC) performs principal role in heat transfer ability of nanofluids. Artificial neural networks (ANNs) have shown promising performance in modeling nanofluids' TC. In this article, two types of ANNs are used for estimating TC of nanofluids with TiO_2 nanoparticles. In this regard, effective factors including particle size, temperature, volume fraction of solid particles and TC of the base fluids are applied at the input of the model. Based on the comparison between the estimated data and the corresponding actual ones, it is concluded that employing multi-layer perceptron (MLP) is superior compared with group method of data handling (GMDH). In the optimal conditions of the networks, the R-squared value of the models based on both MLP and GMDH was 0.999. Moreover, average absolute relative deviations of the mentioned models were around 0.23% and 0.32%, respectively.

Keywords: nanofluid; thermal conductivity; heat transfer; TiO_2 nanoparticles

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1. INTRODUCTION

Nanotechnology that involves the materials in nanometer dimensions has attracted scientists' attention due to its ability in improving different properties of materials [1–4]. This field of science has been widely used in thermal engineering in recent years. Properties of operating fluids, especially their thermal conductivity (TC), have leading role on performance of thermal mediums. Generally, it is preferred to use the fluids with higher TCs in order to intensify heat transfer rate. Use of nanofluids is one of the promising approaches suggested for heat transfer augmentation due to their increased TC [5–8]. Studies have demonstrated that by employing nanofluids in thermal mediums such as heat exchangers and heat pipes, noticeable enhancement can be achieved in thermal performance. In addition to thermal mediums, different energy-related systems will have improved efficiency and reliability by applying nanofluids [9, 10]. By using nanofluids in energy systems with low carbon emission, their performance and reliability can be improved. In fact, use of active techniques like utilization of nanofluids can lead to heat transfer augmentations that result to less energy consumption. Less energy use can indeed be beneficial for our environment leading to less carbon footprint. For instance, according to the review study provided by Reddy et al. on the applications of nanofluids and nanocomposite in solar energy, it was concluded that employing nanofluids can result in significant enhancement of conversion efficiency in comparison with the cases of using pure fluids. In addition to efficiency enhancement, the reliability of clean energy systems is improvable by

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using nanofluids. As an example, Islam et al. [11] investigated the impact of applying nanofluid in thermal management of PEM fuel cell and concluded that employing nanofluid instead of pure fluid can increase convective heat transfer by around 63% which indicates improved reliability of the cooling system. Zhong et al. [12] studied TiO_2 nanofluid inside a mini channel. Two different volume concentrations of 0.5% and 1% were used in their study. It was revealed that utilization of nanofluid can increase TC and viscosity of the 1% nanofluid by 4.2% and 14.9%, respectively. The flow and thermal pattern of the nanofluid was compared with water at different transient phases of before and after transition. An earlier laminar-turbulent transition was observed for the nanofluid compared to the water fluid. In an investigation by Gravndyan et al. [13] water/TiO_2 nanofluid flow was studied inside a microchannel. Different aspect ratios of rib were considered, and its effect on heat transfer was evaluated. It was shown that addition of nanoparticles can increase both friction factor as well as Performance Evaluation Criteria (PEC).

As it was mentioned, the main reason for superior performance of nanofluids in heat transfer compared with the conventional ones is their increased TC. In this regard, several studies concerned modeling the thermophysical properties of nanofluids [14, 15]. In the proposed models different methods have been employed such as artificial neural network (ANN), support vector machine (SVM) and mathematical correlations [16, 17]. Among these approaches, ANNs are very attractive due to their ability in accurate prediction and forecasting the output in complex modes [18, 19]. Esfe et al. [20] applied ANN for estimating TC of Al_2O_3/EG nanofluid by considering the temperature and volume fraction (VF) of solid phase as the inputs. They found that by employing ANN, the maximum deviation of the proposed model did not exceed 1.3%. Vakili et al. [21] used ANN for modeling TC of CuO/water-EG nanofluid by considering the same inputs and found that by using ANN accurate prediction of TC of the nanofluid was possible with R-squared of 0.999. Toghraie et al. [22] employed ANN for proposing a predictive model for TC of SiO_2/EG-water. The maximum value of error in their model was 0.0125, demonstrating the great reliability of the model. Esfe et al. [23] proposed a model on the basis of ANN for estimating the TC of Al_2O_3/water-EG by using temperature and VF as the inputs. In the most appropriate condition, which was obtained by testing different architectures for the network, mean square error (MSE) of their model was around 2.08×10^{-6}. According to the obtained results in the aforementioned studies and other ones in the relevant fields, it can be concluded that using ANN is appropriate for estimating and forecasting TC of various nanofluids. In another study, Esfe et al. [24] used ANN with two hidden layers and eight neurons in each layer to predict Nusselt number and pressure drop of TiO_2 nanofluids with different nanoparticle diameters. The accuracy of prediction of their model was investigated, and it was also shown that increasing Reynolds number and concentration leads to increment of Nusselt number and pressure drop.

Nanofluids with TiO_2 nanoparticles have wide applications in energy-related technologies which are provided in the next section of this article. In this regard, proposing a comprehensive model would be useful for researchers in this field. In this paper, different nanofluids with TiO_2 nanoparticles are considered for TC modeling. In order to attain a model with applicability for different base fluids, TC of the base fluid is used as the input in addition to size, VF and temperature. For comparing the performance of the ANN-based models, two methods including group method of data handling (GMDH) and multi-layer perceptron (MLP) are used. In this study, different models are proposed for TC modeling of nanofluids with TiO_2 and various base fluids. In addition, two different types of networks are assessed to reach the highest accuracy. Furthermore, the architecture of the models is varied to find the network with the maximum reliability in forecasting the considered output.

2. APPLICATIONS OF NANOFLUIDS WITH TIO2 PARTICLES IN ENERGY-RELATED TECHNOLOGIES

Nanotechnology has been used in different forms and materials in various energy systems [25–31]. Nanofluids with TiO_2 particles are among the materials that have been broadly applied in different energy-related technologies. Reddy et al. [32] evaluated the performance of a double pipe heat exchanger by applying TiO_2/ethylene glycol (EG)-water nanofluid and compared its performance with the case of using base fluid. They observed that employing the mentioned nanofluid resulted in 10.73% increment in heat transfer coefficient compared with the condition of using the base fluid. In another study, Hilmin et al. [33] compared the performance of a system composed of thermoelectric that uses vehicle exhaust gas for power generation in cases of using water and TiO_2/water nanofluid as the cooling fluid in cold surface of the thermoelectric unit. They observed that employing nanofluids causes higher power production by the mentioned system which is attributed to more favorable specifications of the nanofluid in term of heat transfer. In addition to the aforementioned systems, using nanofluids with TiO_2 particles can enhance the output of refrigeration system. As an example, Weixue et al. [34] used TiO_2/water nanofluid in an ammonia-water absorption system. They observed that using the nanofluid in the considered system resulted in up to 27% increment in the coefficient of performance (COP).

These nanofluids are useful for improving the efficiency of different renewable energy technologies. For instance, Ebaid et al. [35] used TiO_2/water -polyethylene glycol for thermal management of photovoltaic module. They observed that using the nanofluid led to up to 6.05% increase in the output of the cell, while the corresponding value in case of employing water was around 3.75%. Superior efficiency of the cell by applying nanofluid as coolant was attributed to the better cooling performance. In another work, Subramani et al. [36] assessed the effect of using TiO_2/DI water on the efficiency of parabolic through collector. In this regard, different concentrations ranging from 0.05% to 0.5% were used in the collector. They found that by employing the nanofluid, convective heat transfer could enhanced by up to 22.76%. In addition, they found that the highest efficiency of the collector was obtained by using the nanofluid in 0.2% concentration which was 8.66% higher in comparison with the case of using pure water. Moravej et al. [37] applied TiO_2/water nanofluid in a flat-plate solar collector that had symmetric structure. Three concentrations of the nanofluid including 1%, 3% and 5% wt were considered in their work. It was noticed that utilizing the nanofluid instead of water led to maximum gains of 17.41%, 27.09% and 33.54% for the mentioned concentrations, respectively. Hosseini et al. [38] applied TiO_2/water nanofluid in a U type evacuated solar collector. In this work, two type of nanostructures including wire and spherical-like were tested. They noticed that employing the nanofluids with wire and spherical-like shapes led to efficiency enhancement of up to 21.1% and 12.2%, respectively. Kumar et al. [39] used water with and without TiO_2 nanoparticles in a solar heater. The maximum efficiency of their system in case of using water and nanofluid were 55% and 58%, respectively, indicating more favorable performance of the nanofluid in the system in comparison with water. In addition to the solar systems, nanofluids with TiO_2 particles can be applied in other clean energy technologies for heat transfer enhancement such as geothermal heat exchangers, thermal management units of fuel cells, etc. [40, 41].

3. METHODOLOGY

In the current study, GMDH and MLP which are among the most conventional types of ANNs, are used for estimating the TC of the nanofluids. In this section, these algorithms are shortly explained.

3.1. GMDH neural network

GMDH neural network has set of neurons that are created from connection of different pairs through a quadratic polynomial. Method of grouping numerical data is a statistical technology that aims at overcoming statistical and neural network weaknesses. What makes GMDH as a heuristic technique is making models for complex systems with high degree of regression. This has some advantages over classical models. GMDH was first introduced by Ivakhnenko. General form of connection between input and output variables can be expressed by a polynomial function as follows [5, 42]:

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \dots \quad (1)$$

This equation is called Ivakhnenko polynomial [5, 42]. By using regression techniques, the unknown coefficients of a_i are obtained in a way that the difference between real values of output y and the calculated values of $\hat{y}$ becomes minimum for each input pair of x_i and x_j. By using the above equation, a set of polynomials is produced and their unknown coefficients are obtained by using least squared technique. For each created neuron, the coefficients of equations are obtained in order to minimize the overall error for optimal adaptation of inputs to all pairs of input–output sets. The schematic of GMDH neural network is shown in Figure 1.

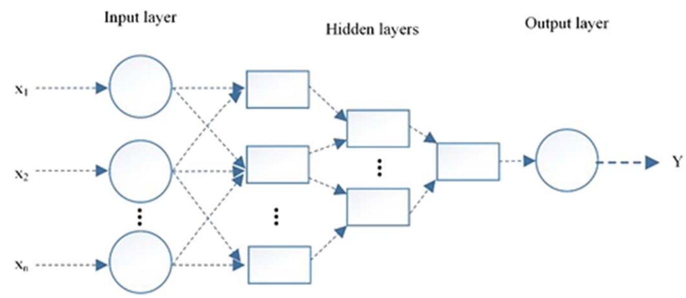

Figure 1. *Schematic of GMDH neural network.*

3.2. MLP neural network

MLP network is created from multi layers and each layer produces the input of the next layer in the form of feed-forward. The structure of a MLP network is determined through number of layers, number of neurons in each layer, stimulus function, training method, algorithms for correcting weights and type of the model. In the current study, one hidden layer with different numbers of neurons is used. Levenberg–Marquardt algorithm is considered for training algorithm as it has fast convergence. The algorithm changes the network weights and bias values in such a way that the network performance function decreases more rapidly:

$$x_{k+1} = x_k - \alpha_k g_k. \quad (2)$$

In this equation x_k is weights and bias vector in k_{th} iteration, α_k is the training rate at k_{th} iteration and finally g_k is the gradient in k_{th} iteration. To get a better and faster training, Levenberg–Marquardt is developed as follows:

$$x_{k+1} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e \quad (3)$$

where J is the Jacobian matrix of the multivariate error function of the network, e is the error vectors of the network and I is the identity matrix and μ is a scalar. More details of these approaches can be found in References of [43–46]. The schematic of MLP neural network is shown in Figure 2.

4. RESULTS AND DISCUSSION

To achieve a comprehensive model with applicability for different nanofluids containing TiO_2 nanoparticles, various base fluids are considered here. In this regard, data are extracted from various references [47–49]. In order to consider the effect of base fluid in the model, its TC in 30°*C* is added to the inputs. Other inputs are temperature, VF and nanoparticle size. The base fluids of

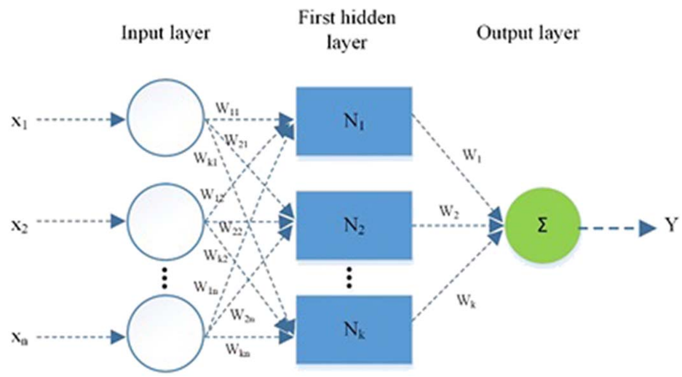

Figure 2. *Schematic of MLP neural network.*

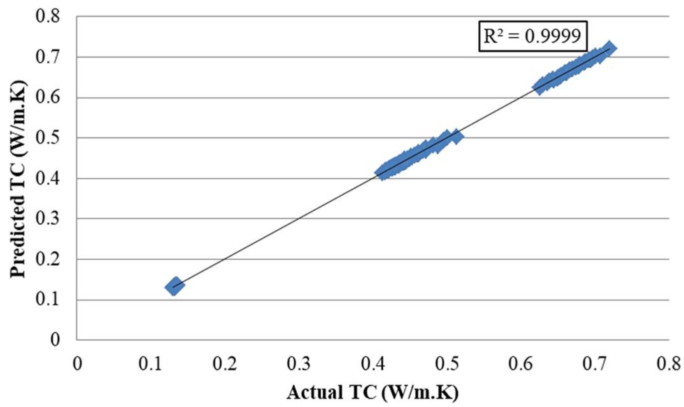

Figure 3. *Predicted TC vs. actual TC by using GMDH.*

the considered nanofluids are water, mixtures of water and EG and diathermic oil. GMDH, as the first algorithm is used for estimating the TC of the considered nanofluids. In Appendix I, the obtained correlation between the inputs and the TC is represented. In this equation, x_1, x_2, x_3 and x_4 are VF, nanoparticle size, base fluid TC and temperature, respectively. In Figure 3, the forecasted data by GMDH-based model are compared with the corresponding actual ones obtained in the experimental studies. In case of utilizing GMDH as modeling approach, R-squared is 0.9999, revealing noticeable reliability of the model in predicting TC.

In order to get more considerable insight into the performance of the proposed model, relative deviation of each data index is determined. As illustrated in Figure 4, the maximum absolute value of relative deviation in case of using GMDH is around 2%. Moreover, it can be found that the relative deviation of the model for the majority of the data is in range of $\pm 0.5\%$,which is another reason for the accuracy of the proposed model.

Architecture of MLP ANN is very crucial in its performance. In this regard, different numbers of neurons in hidden layer are tested. It should be mentioned that a network with single hidden layer is used in this study since the problem is not very complex and previous studies have shown that for such problems, using a hidden layer is adequate [14]. In this research, the number of

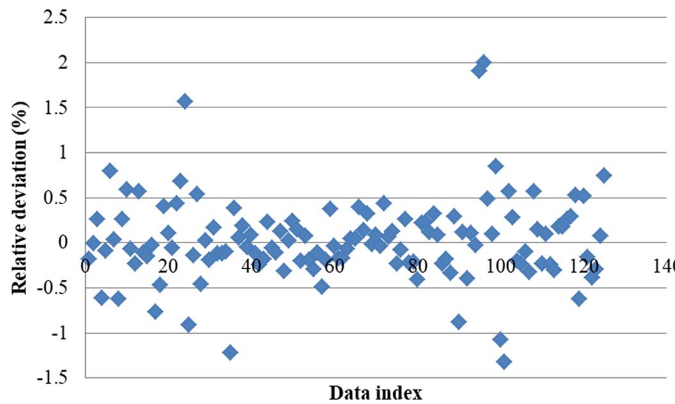

Figure 4. *Relative deviations of data for GMDH-based model.*

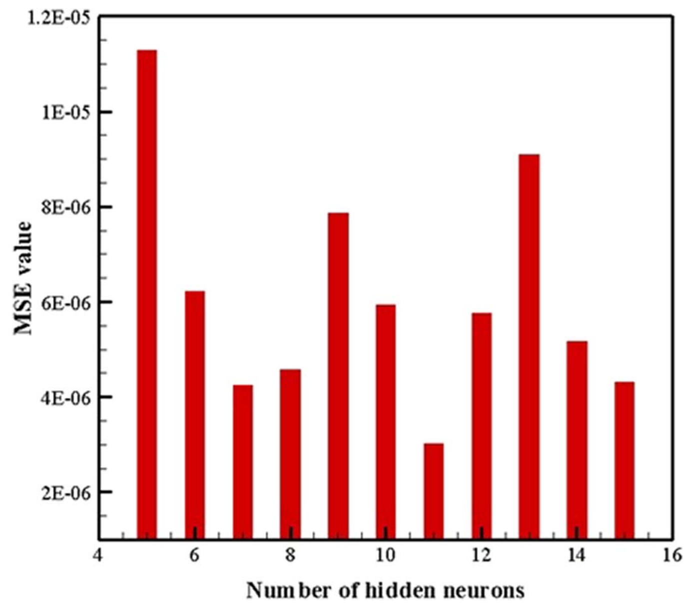

Figure 5. *MSE values for different numbers of neurons in hidden layer.*

neurons varies between 5 and 15, which is an appropriate range according to the previous studies in the similar subjects [14]. In Figure 5, MSE values for the tested architectures are represented. According to the data represented in this figure, using 11 neurons in the hidden layer leads to the most appropriate model in term of accuracy.

Since using 11 neurons in the hidden layer leads to the highest accuracy, this architecture is considered for analysis. In Figure 6, the obtained data by this structure is compared with the actual ones represented in the experimental studies. As shown in this figure, R-squared is equal to 0.9999. This value of R-squared, which is very close to 1, shows model's perfect accuracy.

Similar to the previous condition, relative deviation of the predicted data compared with the corresponding actual ones are compared here. As shown in Figure 7, the maximum absolute deviation of the data in case of using MLP is around 1%, which is lower than the corresponding value in case of employing

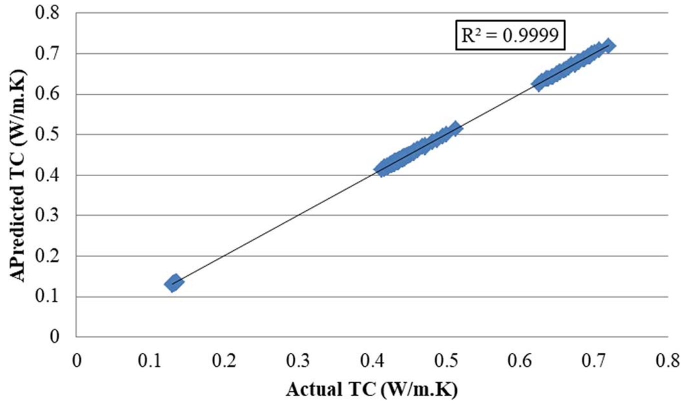

Figure 6. *Predicted TC actual TC by using MLP.*

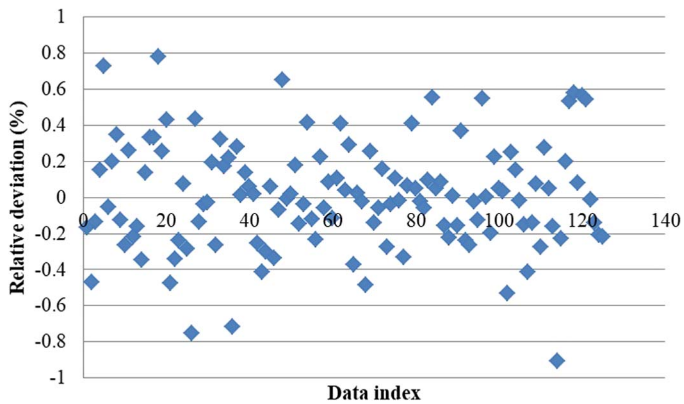

Figure 7. *Relative deviations of data for MLP-based model.*

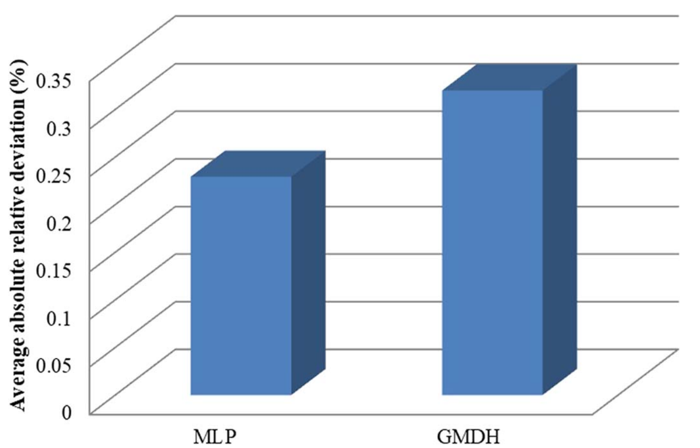

Figure 8. *Average absolute relative deviations of the models.*

GMDH and indicates its more appropriateness in term of relative deviation.

As final criterion, average absolute relative deviation is used for comparing the models. Based on the determined relative deviations of the applied models, this index is calculated for both of them. As shown in Figure 8, this value is around 0.23% and 0.32% for the models based on MLP and GMDH, respectively.

5. CONCLUSION

Nanofluids with TiO_2 particles are applicable in different devices and systems specially the ones useful in renewable energy and thermal management systems. In the present study, two types of ANNs including GMDH and MLP are used for TC modeling of the nanofluids containing TiO_2 particles. In this regard, base fluid TC, temperature, VF and size of particles are applied at the inlet of the models. Both trained models had prefect accuracy with R-squared of 0.999. In addition, according to the obtained values of relative deviations, it is concluded that using MLP for training network for estimating TC of the nanofluids led to lower average absolute relative deviation, around 0.23% for MLP and 0.32% for GMDH, which means higher confidence of this approach. Furthermore, it was demonstrated that the highest value of absolute relative deviations was around 2% and 0.9% for the models that used GMDH and MLP, respectively.

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