Smart modeling by using artificial intelligent techniques on thermal performance of flat-plate solar collector using nanofluid

Milad Sadeghzadeh1 | Mohammad Hossein Ahmadi2 | Mostafa Kahani3 | Hossein Sakhaeinia4 | Hossein Chaji5 | Lingen Chen6

1Department of Renewable Energies, Faculty of New Sciences and Technologies, University of Tehran, Tehran, Iran
2Faculty of Mechanical Engineering, Shahrood University of Technology, Shahrood, Iran
3Faculty of Chemical and Materials Engineering, Shahrood University of Technology, Shahrood, Iran
4Department of Chemical Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran
5Agricultural Engineering Research Department, Khorasan Razavi Agricultural and Natural Resources Research and Education Center, AREEO, Mashhad, Iran
6Institute of Thermal Science and Power Engineering, Wuhan Institute of Technology, Wuhan, China

Correspondence
Mohammad Hossein Ahmadi, Faculty of Mechanical Engineering, Shahrood University of Technology, Shahrood, Iran.
Emails: mohammadhosein.ahmadi@gmail.com and mihosein.ahmadi@shahroodut.ac.ir

Lingen Chen, Institute of Thermal Science and Power Engineering, Wuhan Institute of Technology, Wuhan, China.
Emails: lingench@hotmail.com and lgenchina@yahoo.com

Abstract
In the current study, Multilayer Perceptron Artificial Neural Network (MLP-ANN) mode, Radial Basis Function Artificial Neural Network (RBF-ANN), and Elman Back Propagation Neural Network (Elman BP-ANN) are developed to predict the thermal efficiency of a flat-plate solar collector. TiO2 (20 nm)/water nanofluids are prepared using two-step method and used in the designed solar system. All experiments are done in Mashhad city, Iran (Longitude/Latitude: 36.2605°N, 59.6168°E), according to EUROPEAN STANDARD EN 12975-2 as a quasi-dynamic test (QDT) method, and the solar collector is exposed to the south with the tilt angle of 55°. Three levels of inlet temperature (ambient air temperature, 52 and 74°C), 3 levels of volumetric flow rate (36, 72, and 108 L/(m².h)), and 4 levels of nanofluid concentrations (0, 0.1, 0.2, and 0.3 wt.%) are considered as the input data, and the thermal efficiency of the solar system is calculated. According to the output results of developed models, the best prediction of thermal performance is obtained by MLP-ANN model, although other generated models are also able to predict the efficiency of the solar collector with appropriated accuracy.

KEYWORDS
flat-plate solar collector, nanofluid, neural network, thermal efficiency
1 | INTRODUCTION

Integration of renewable energies assists energy systems to reduce environmental contamination significantly. Several factors such as energy cost, energy consumption rate, and sustainable availability lead the societies to follow an alternative solution for replacing fossil-based energy with a minor harmful effect on the environment. Utilization of renewable energy in the energy conversion systems, such as the sun or wind energy can be a solution to these challenging issues. It is conceived renewable energies specifically solar energy, be a major origin of providing energy demands of human beings activity. Although solar energy is an everlasting and the most available source of energy, it has some negative features such as lower density and its intermittent inherent. Therefore, a storage system should be devised in order to gather solar energy when it is available for further consumption. Solar water heater (SWH) is one of the presented storage technologies, which uses water as a storage medium. Hence, the flat-plate solar water heater (FPSWH) was developed and used as a direct utilization of solar energy for water heating purposes. The most challenging issue in the utilization of solar water heaters, similar to other energy conversion systems, is the thermal efficiency factor. Therefore, several investigations have been carried out to boost up thermal efficiency and enhance the performance of FPSWHs. Heat transfer performance can be enhanced through active and passive approaches. In the active method, the presence of a bias force is vital; meanwhile, no external force is needed in the passive approach. The heat transfer rate can be enhanced by introducing nanofluid as the working fluid of the heat exchangers. The application of nanofluid in the heat exchangers has been widely investigated in the literature; however, there is a gap in the utilization and effect of nanofluid for thermal enhancement of flat-plate solar collectors. Das et al. stated that nanofluids have this feasibility to be utilized in the solar collectors in order to boost up the heat transfer rate and to augment the energy density. Natarajan and Sathish recommended that nanofluids were more practical in solar water heaters instead of typical working fluids and enhanced thermal efficiency. Tiwari et al. performed a theoretical study on the influence of applying Al2O3 nanofluid in a flat-plate solar collector. In addition, the authors also analyzed the impact of varying the mass flow rate and changing the volume concentration of Al2O3 nanofluid and monitoring their effect on the performance of solar collectors. It was reported that the thermal efficiency of solar collectors could be increased to 31.64% by applying Al2O3 nanofluid at the volume concentration of 1.5%. Otanicar and Golden studied the utilization of a hybrid nanofluid composed of silver, graphite, and carbon nanotubes for being used in solar collectors. It was found that the hybrid nanofluid enhanced the thermal efficiency of the flat-plate solar collectors by 5%. Based on the carried out investigations, the value of the thermal efficiency was proportional to the volume concentration of nanofluids in the working fluid. Yousefi et al. analyzed the feasibility of Al2O3 and MWCNT nanofluids in the flat-plate solar collectors. The experiments declared that applying Al2O3 and MWCNT in the working fluid boosted up the thermal efficiency to 28% and 35%, respectively. Colangelo stated that by enhancing the stability of Al2O3 nanoparticles and retarding the sedimentation process, the performance of flat-plate solar collectors is improved because of increasing the heat transfer coefficient by 25%. Rahman et al. evaluated the natural heat transfer mechanism of a solar collector with a triangular layout when different nanofluids were applied, Cu/water, Al2O3/water, and TiO2/water, respectively. It was monitored from the experiments that the replacement of Cu/water nanofluid at a volume concentration of 10% enhanced the heat transfer rate by 24%. Parvin et al. investigated the effect of utilizing Cu/water and Ag/water nanofluids on the natural convection mechanism for a solar collector and modified the Nusslet number formulation. The authors have limited their model by defining a boundary for the Reynolds number and the highest volume concentration of nanofluid, 1000 and 3%, respectively. Chaji et al. examined the performance of a flat-plate solar collector through defining an experiment by applying TiO2 nanofluid at various concentrations. It was reported that the efficiency of the solar collector was increased when a working fluid at the concentration of 0.3% was employed. Zamzamian et al. investigated the performance of flat-plate solar collectors by applying Cu-synthesized/EG nanofluid. It was demonstrated that increasing the concentration of nanoparticles led to an augmentation in efficiency. Moghadam et al. performed an experiment to determine the optimal value of mass flow rate for nanofluid flow, CuO/water, in a flat-plate solar collector to obtain the highest thermal efficiency. Kilic et al. examined the thermal performance of a flat-plate solar collector by applying TiO2 nanofluid. Taylor et al. evaluated the utilization of nanofluids in collectors with a high intensity of solar energy. It was found that the efficiency of solar dish collectors was increased by 10% when nanofluid of graphite at a volume fraction of 0.125% was used. However, the application of nanofluids in the solar water heater, specifically flat-plate solar collectors are still underdeveloped and immature. Flat-plate solar collectors are the most conventional type of devices in the fields of renewable energy utilization. Hence, increasing the efficiency of these collectors is a common target for scientists who are working in the renewable energy industry. One of the recent ideas in this field is to replace conventional working fluids with novel nanofluids. Colangelo et al. experimented and simulated the effect of applying Al2O3 nanofluid at different volume concentration on the performance of solar thermal collectors. It was reported that insertion of nanofluid at volume concentration of 0.03 increased the thermal efficiency up to 7.5%.
Various investigations have been carried out to obtain an optimized energy system by altering the operational parameters. For this purpose, energy systems are modeled and simulated through optimization methods such as an artificial neural network (ANN). Several studies have been done which employed smart techniques to model the efficiency of PV/T collectors. Kalani et al. utilized artificial neural network (ANN) and particle swarm optimization (PSO) technique to propose a model for estimating the performance of a PV/T solar collector. The working fluid was ZnO/water nanofluid, and 130 experimental data sets were extracted through experiments to be used in the modeling procedure. It was reported that among various considered ANN approaches, ANFIS (adoptive neuro fuzzy inference system) and RBF (radial basis function) were more accurate in estimating the outlet temperature of the PV/T working fluid and its corresponding efficiency. Al-vaeli et al. compared the result of applying nanopcm and nanofluid in the PV/T setup and concluded that utilization of nanopcm material/water and nanofluid of SiC/water improved the electrical current and also the electrical efficiency. In addition, the authors developed some ANN-based models to estimate the efficiency of the system and monitored an acceptable agreement between experimental data and estimated data from ANN methods.

In this study, TiO₂/water nanofluid will be used as the working fluid in a flat-plate heat exchanger to evaluate the thermal efficiency of the solar system. Inlet temperature and flow rate of working fluid and the weight concentration of nanofluid will be considered as the input data, and the thermal efficiency of the solar system will be considered as the output data. Based on the obtained results from various introduced topologies in this study, that is, MLP, Elman, and RBF, all of these machine-learning methods are suitable ways to predict the thermal performance of nanofluid in solar systems.

2 MATERIALS, METHODS, AND EXPERIMENTAL RESULTS

Titania powders (TiO₂ with rutile structure) are applied into double distilled water through two-step approach to obtain solutions with different concentrations of nanoparticles, 0.1, 0.2, and 0.3 wt. %, respectively. The size and surface area of the used TiO₂ nanoparticles are 20 nm and 40 m²/g, respectively. Aggregation and deposition of nanoparticles due to the surface tension are the major challenging issues in the application of nanoparticles. The surface tension is caused since nanoscale materials have a large volume ratio. Therefore, in order to surmount this issue surfactants are applied. Although surfactants such as Triton X-100, cetyl trimethyl ammonium bromide (CTAB), Tween-20, and Tween-80 make the nanofluid more stable, due to the formation of foams or air bulbs, lower the efficiency of the solar collectors. Thus, utilizing and fabrication of pure nanofluid is preferable.

As shown in Figure 1, the experiment setup consists of a solar collector, nanofluid container, circulation system, cooling heat exchanger, rotameters for regulating the flow rate and solar power meter. The main part of the system is a flat-plate heat exchanger. The length, width, and thickness of absorber plate are 0.5, 0.2, 0.001 m respectively and copper metal is used for fabrication. The inner diameter of the riser tube is 0.003 m while the outer diameter is 0.003 m. A 0.005 m thickness of glass cover is applied over the solar receiver part. In addition, 0.050 thickness of Rockwool is applied to the back of the system.

The bulk temperature of working fluid is measured by two mercury bar thermometers (with an accuracy of ±0.1%) which are inserted into the calming and mixing chambers of the flow at the inlet and the outlet of solar collector. When the nanofluid or distilled water as the working media leaves the test section, it pumps to a heat exchanger for cooling, then directed into a rotameter, and finally flows back to the reservoir tank. A TES 1333 solar power meter is used to measure the solar radiation (Gt), and an anemometer (PROVA AVM-03) is applied to provide accurate measurements of wind velocity. All experiments are done in Mashhad city, Iran (Longitude/Latitude: 36.2605°N, 59.6168°E), according to EUROPEAN STANDARD EN 12975-2 as a quasi-dynamic test (QDT) method, and the solar collector is exposed to the south with the tilt angle of 55°. It usually takes 20 minutes to observe state data from the setup.

The experiments are done for 3 levels of inlet temperature (ambient air temperature, 52 and 74°C), 3 levels of volumetric flow rate (36, 72 and 108 L/(m² h)) and 4 levels of nanofluid concentrations (0, 0.1, 0.2, and 0.3 wt.%). The thermal efficiency of the solar system is calculated from obtaining the ratio of useful energy gain to incident radiation:

\[
\eta = \frac{\dot{m}C_p(T_o-T_i)}{A_s G_t} \tag{1}
\]

where \(\dot{m}\) and \(C_p\) are the mass flow rate and heat capacity of the employed working fluid, respectively. Classical equation can be used for evaluation of heat capacity of water and nanofluid. \(A_s\) is the surface area of solar collector and \(G_t\) is global solar radiation, which varied between 900 and 1000 W/m².

A smooth three-dimensional plot is plotted in Figure 2 to show the effect of volumetric flow rate and weight percent of nanofluid on the thermal efficiency of the designed solar system at 30°C. As can be concluded from this figure, the efficiency is enhanced by increasing the concentration as well as the flow rate of nanofluid. Improvement of thermal performance of nanofluid in comparison with pure water is observed. The enhancement of thermal performance with an
increase in the nanoparticle weight concentration as well as the flow rate is mainly due to higher thermal conductivity and convective effects in nanoparticle suspension. In addition, at higher flow rates, the random movement of particles intensifies considerably which leads to migration phenomena. The maximum thermal efficiency obtained during the experiments is observed at the flow rate of 108 L/(m² h), 0.3 wt.% of nanofluid and \( T = 30^\circ C \) is around 55.76%.

3 | ARTIFICIAL NEURAL NETWORK MODELING

3.1 | Efficiency estimation based on the multilayer perceptron neural network (MLP)

The multilayer perceptron neural network considered 50 sets of data including temperature, concentration, and mass flow rate as input and, consequently, 50 data from the corresponding efficiencies as the output of the model. Here, a dual neural network model in addition to a hidden layer with a various number of neurons and an output layer is formed. In this neural network, training algorithms deliver the training data to the neural network. The network continuously repeats and updates the weights and orientations until the anticipated values are matched to the desired values. In the modeling procedure, the feed-forward back propagation algorithm (FFB), the Levenberg-Marquardt training (TRAINLM) method, and the functional performance criteria of MSE (mean squared error) are utilized. The performance function of MSE is a function used to calculate the error in the network training process. In addition, in this neural network, the TANSIG transfer function and LEARNGDM learning function are employed. The overall topology for estimating the efficiency of the solar collector in this neural network model is illustrated in Figure 3.
In this structure, the number of neurons in the input layer is 3, representing the number of inputs to the network inputs (three inputs including temperature, concentration, and mass flow rate). The number of neurons in the hidden is assumed to be 10, by default. The network output layer is a single layer, which is the same as process analysis.

In the process of data interpretation by the neural network, the data are divided into three groups of training, validation, and test, respectively. In this process, the specific output is used for learning and regulation of communication weights of the corresponding input among neurons. At this point, 70% of the data is randomly assigned to training, 15% for monitoring or verification, and 15% for testing or evaluation of the artificial neural network. The neural network completes the learning process through training data and verifies the quality of network learning. Finally, with the help of test data, the network can be evaluated to assess its accuracy in the estimation of different situations. For a proper generalization of the network, it must be prevented from overtraining.

The mean squared error during the training process is depicted in Figure 4. Obviously, by increasing the frequency, the error value is gradually decreased for all three categories. With the progress of the algorithm at each replication stage, the mean squared error for the verification data is re-calculated. The algorithm will not stop until the verification error decreases, and training continues. When the validation error does not occur in 6 consecutive repetitions, the training is stopped. This number is the stop training indicator, which is adjustable in the software. This number is known as the validation check, and the default number is 6 in the software.

Enlarging the validation check number, although decreased the error of the training data, on the other hand, the network goes to over-fitting and the test data error increases quickly and the network goes to memorize and reduces its generalization feature.

Over-fitting is a term commonly used in the neural network and refers to a situation in which the network, due to overtraining, brings its error to zero for training data, and its prediction range is limited to the data that is close to the training data. In other words, network prediction for data that is not used in the learning process would be out of range (the network that is over-fitted does not have a good prediction of the test data).

The point where the verification error reaches its minimum is considered as the output. In Figure 4, before the repetition number 5, the network error for the training data and the validation process is declining, and from repetition 5, the validation error is incremental, while the training data error continues to be declining. From repetition number 5-11 (6 consecutive repetitions), the validation error has an increasing trend, so the training algorithm ends and repetition number 5 is considered as an output. In other words, the training process is stopped if the evaluation set error is raised in 6 consecutive repetitions. This pause occurs in repetition number 11.

It should be noted that the algorithm calculates the mean squared error as follows:

\[
MSE = \frac{1}{N_e} \sum_{i=1}^{N_e} \left( \frac{N_{RNN} - N_{Real}}{\text{Ne}} \right)^2
\]

where \(N_{RNN}\) indicates the estimated efficiency through the neural network, \(N_{Real}\) is the actual efficiency, and Ne represents the total number of samples.

The regression line of R (correlation coefficient) for all three categories of training, validation, and test is depicted in Figure 5. As can be seen from this figure, a high correlation coefficient indicates the proper performance of the neural network in the prediction of the efficiency. The actual value of the efficiency and the calculated value through the modeling are compared and demonstrated in Figure 5. Ideally, when the network error is zero, all points are placed on the

![Figure 3](image1.png)

**Figure 3** The topology of the multilayer perceptron neural network in the prediction of efficiency

![Figure 4](image2.png)

**Figure 4** Mean squared errors in the various repetitions of the training process
line (Y = T) (the bisection of first and third quadrants). In practice, there is a small amount of error that causes the points to be scattered up and down of this line. The equation of the best passing line from the points of this graph with its correlation coefficient is given in Figure 5. The coefficient of determination, $R^2$, is calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (NR_{NN} - NR_{Real})^2}{\sum_{i=1}^{n} (NR_{NN} - NR_{ave})^2}$$

where $R^2$ is the coefficient of determination, $NR_{NN}$ represents the estimation efficiency obtained from the model, $NR_{Real}$ indicates the measured efficiency, and $NR_{ave}$ denotes the average values of the measured efficiencies.

The histogram diagram of the error is depicted in Figure 6. The error value is defined as the difference between the actual value and the output value of the neural network model. The error value can be either positive or negative. If one divides the entire error interval into 20 equal parts, then calculate the amount of each interval and draw up the three classes of training, validation, and test, then, the histogram diagram of the error is obtained. In fact, this diagram displays the frequency of the model prediction error in each subinterval. The zero-error line is depicted in Figure 6 with an orange line. The data with a near zero error are distributed around this line. The blue color shows the frequency of training data. The green color indicates the frequency of validation data, and the red color represents the frequency of test data, respectively.
The obtained results of the neural network modeling and the actual results are plotted for the total data (62 data) as illustrated in Figure 7. Based on this figure, there is an acceptable agreement between model results and actual measurements.

The mathematical equation of this structure is in the form of the following equation. In fact, the neural network model for calculating efficiency is as follows:

$$\text{Efficiency} = ([LW] \ast \tanh ([LW]_{b,3} \ast \begin{bmatrix} C \\ T \\ Q \end{bmatrix} + [b]_1) + [b]_2)$$

During the training process, weights and bias of the network are systematically updated to match the output data.
from the neural network with the experimental value obtained from the laboratory results (the weights are the IW and LW matrices, and the bias are the matrices of \( b^1 \) and \( b^2 \)). In other words, the error function is minimized during training in continual repetitions. As previously stated, the purpose of modeling with the help of the neural network is to build a system that can efficiently predict the output data using input data \((C-T-Q)\). When the error function reaches its minimum, neural network training is finished, and from now on, the neural network can be used to predict the output variables by using the input variables.

### 3.2 Efficiency estimation based on the Radial Basis Function neural network (RBF)

The topology of this kind of neural network is depicted in Figure 8. The first layer is the input layer, and it only plays the role of transferring data to the network. The next layer is the hidden layer of the network, which consists of a large number of neurons in these types of networks. The features of this kind of neural network are a fast learning process, the possibility of training of the network with the least initial data set, determination of the optimal size of the network by its own algorithm, and also the absence of a local minimums problem.

### 3.3 Efficiency estimation through Elman Back Propagation neural network

Similar to multilayer perceptron artificial neural network, required codes are written in the toolbox of the MATLAB software; temperature, concentration, and mass flow rate are the input data and efficiency, the output data, which are introduced into the MATLAB software. The topology and the mean squared errors in the various repetitions of the training process for this type of neural network are depicted in Figures 9 and 10, respectively. Also in this neural network, the TANSIG transfer function, the TRAINLM training function, and the LEARNNGDM learning function are utilized.

Table 1 lists the results of predicted efficiency based on the three different topologies. It is monitored that the multilayer perceptron artificial neural network has the best prediction compared to the actual measured value of efficiency (ie, 37.9% in the design conditions).

### Table 1 The prediction values based on different neural network models

| Neural network type | Performance function | Training function | Learning function | Transfer function | Estimated efficiency (%) |
|---------------------|----------------------|-------------------|------------------|------------------|-------------------------|
| MLP                 | MSE                  | TRAINLM           | LEARNNGMD        | TANSIG           | 38.4                    |
| Elman               | MSE                  | TRAINLM           | LEARNNGMD        | TANSIG           | 37                      |
| RBF                 | –                    | –                 | –                | –                | 33.28                   |

### 4 Conclusion

Neural network modeling has many advantages, including simplicity, optimal accuracy, genericity, and high speed. The neural network model is a suitable method for modeling complex systems, such as heat transfer and solar processes. In this study, TiO₂/water nanofluid is used as the working fluid in a flat-plate heat exchanger to evaluate the thermal efficiency of the solar system. Inlet temperature and flow rate of working fluid and the weight concentration of nanofluid are considered as the input data and the thermal efficacy of the solar system is considered as the output data. Based on the obtained results from various introduced topologies in this study, MLP, Elman, and RBF, all of these machine-learning methods are suitable ways to predict the thermal performance of nanofluid in solar systems. However, among them, the multilayer perceptron artificial neural network (MLP-ANN) shows the best prediction based on the actual measured value of efficiency for the flat-plate solar collector. The value of \( R^2 \)-squared by MLP model is obtained to be 0.960.

### NOMENCLATURE

- \( A_c \): Surface area, \( m^2 \)
- \( b \): Bias
- \( C \): Weight concentration, \%  
- \( C_p \): Heat capacity, \( \text{kJ/kg } \degree \text{C} \)
- \( G_t \): Global solar radiation, \( \text{W/m}^2 \)
- \( H \): Efficiency, \% 
- \( \dot{m} \): Mass flow rate, \( \text{kg/s} \)
- \( \text{MSE} \): Mean squared error, \% 
- \( \text{NR}_{\text{ave}} \): Average efficiency, \% 
- \( \text{NR}_{\text{NN}} \): Estimated value of efficiency, \% 
- \( \text{NR}_{\text{Real}} \): Measured value of efficiency, \% 
- \( Q \): Volumetric flow rate, \( \text{L/(m}^2 \text{ hr)} \)
- \( R^2 \): Coefficient of determination, \% 
- \( T \): Temperature, \( \degree \text{C} \)
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