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Modeling the Effect of Boehmite Nanofluid on Outlet Fluid Temperature in a Solar Flat-Plate Collector Using ANN and SVR

Lida Dhlaghi[1], Hekmat Rabbani[1], Esmaeil Mirzaee-Ghaleh[1], Kamran Kheiralipour[2]

[1] Mechanical Engineering of Biosystems Department, Razi University, Kermanshah, Iran.
[2] Mechanical Engineering of Biosystems Department, Ilam University, Ilam, Iran.

Corresponding author: hrabbani47@razi.ac.ir

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ABSTRACT

Designing solar heating systems is important. This study dissolved boehmite nanofluid (ALOOH) in water and used it in a solar heater with a flat plate collector. The solar flat plate collector outlet temperature was higher in this case. The outlet fluid temperature was predicted using an artificial neural network and support vector regression methods. Data collection was conducted for 18 days in July and August in Kermanshah city (47.7N, 34.23 E). The nanofluid concentration was set to 0.2 wt%. Two series of input were considered:• Operator fluid type, flow, time, environment, and input fluid temperatures,•Operator fluid type, flow, time, environment, input and outlet fluid temperatures, the flat plate collector temperature, the temperature of the lower point of the collector, and the temperature of the glass shield.The results indicated that the ANN method was more powerful in predicting the solar heater outlet temperature. Increasing the input factors, the accuracy of the ANN method was also enhanced in a way that its accuracy was 99.7619 for the first series, which increased to 99.8709 for the second one. A comparison of the ANN results with those of the SVR method showed the superiority of the ANN method.

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INTRODUCTION

Combustion of the fossil fuel for releasing their chemical energy is the main source of greenhouse gas emission, among these gases, carbon dioxide has a major role in global warming (Tuller, 2017). The urge for limiting the increase of the global mean temperature to prevent dangerous climate change, development of low-carbon technologies such as solar and wind power has become one of the priorities of many countries (Palage et al., 2019). Numerous studies have addressed the alternative renewable energy sources due to a reduction if traditional energy sources and increase of their price (Thirugnanasambandam et al., 2010). Solar energy is one of the renewable sources of energy which is now one of the most popular sources of energy (Ahmed et al., 2009); it is predicted that it will be the most used source of energy by 2050.

The technical feasibility and economic application of the technologies required for the use of solar energy in a specific place depend on solar irradiation and access to solar sources. Annual average solar exposure of Tehran province (center of Iran, also it's capital) is about 4.92 kWh/m^2 per day.

Such an abundance provides the condition to develop solar energy systems (solar plants and solar heating systems) which are attractive alternatives for conventional fossil fuel plants (oil and coal) (Zeng & Qiao, 2013). Various methods have been developed to use this renewable source of energy; heating water by solar water heating systems is the most economical and feasible method. Flat plate collectors are the most common solar collector which possesses a solar plate placed inside a simple chamber. It can use both direct and scattered solar radiation. Flat plate collectors have been extensively applied in providing domestic hot water in cases where the required temperature is less than 100 (Sen, 2008).

The collector is the major component of a solar energy-based system. The collector absorbs the solar radiation and converts it into the heat. This heat will be then transferred to the fluid circulating inside the collector (usually, water, air or oil). Therefore, the solar energy in the circulating fluid could be directly transferred to the hot water or air conditioning means or stored for application in night or cloudy days (Tian & Zhao, 2013). The most common fluid is water. Water has numerous advantages: it is inexpensive and accessible with relatively high specific heat capacity. It, however, suffers from limitations such as freezing in cold weather and boiling at relatively low temperatures which may result in corrosion (Mahian et al., 2013). Nanofluids can be used to enhance the heat transfer rate in the heating systems. Due to the presence of suspended particles, nanofluids can exhibit better heat conductance compared to the ordinary ones. the size of these particles is set in nanoscale which can result in higher stability and contact surface for heat transfer as well as lower weight (Sinn, 2005).

Artificial neural networks (ANNs) have been widely employed in different problems including prediction. Yaïci et al. investigated ANNs to determine the efficiency of solar water heating systems and examine the effect of the number of input variables. They employed 3 ANNs with 7, 8 and 9 input variables to predict the efficiency and used the empirical data to make sure of the proper architecture of the ANN. Although the accuracy of their proposed model decreased by a decline of the input variables their model still represented a good accuracy for efficiency prediction (Yaïci et al., 2015). Gorjian et al. used the geographical parameters of a theoretical study to investigate the plate parabolic collector. They considered sun radiation, wind speed angle, ambient temperature, wind speed and the absorbing pipe temperature at the input variables and reached high accuracy in collector efficiency prediction (Gorjian et al., 2015). Using the Levenberg–Marquardt algorithm, Benli predicted the nonlinear behavior of the solar collector. Comparing with the empirical results and those obtained by ANN, he proved that the mentioned algorithm has acceptable accuracy (Benli, 2013). Support vector regression is one of the other smart methods used for different fields including prediction. Ramedani et al. investigated the radial basis function (RBF)-based support vector estimator for predicting global solar radiation. Mean square error calculation and determination of ANN, ANFIS, SVR-RBF, and SVR-poly methods and their comparison showed that SVR-RBF has higher accuracy (Ramedani et al., 2014).

In the current study, the ability of artificial intelligence methods (support vector regression and artificial neural network) in predicting the solar collector outlet temperature was investigated. A precise method not only can optimize different parameters, but it can also present the most suitable prediction method.

MATERIALS AND METHODS

To predict the outlet fluid temperature of the flat plate solar collector, the required data were first collected and prepared.

Data collection was conducted in Kermanshah, Kermanshah province in July and August (47.7N; 34.23 E).

The studied system was a flat plate solar collector equipped with a closed-circuit circulation system in which the active fluid was employed in three flow levels using a variable flow pump.

The applied flat plate solar collector model was manufactured by Solar Polar Company, IRAN, as shown in figure 1.

This collector has 6 narrow copper tubes with a thickness of 1 mm for fluid circulation which passes through 6 aluminum sheets (w:15 cm; l:180 cm, t=0.5 mm) with an absorption coefficient of 0.81 serving as solar energy absorbent.

The solar water heating apparatus walls were made of Galvanized iron with 4 wheels.

Regarding the collector surface, the system tank was made in a cylindrical shape from Galvanized iron with a thickness of 3 mm and height and a diameter of 100 and 50 cm, respectively in the double-wall form with total volume of 120 L.

The collector was aligned toward the south with a slope proper (31-35 degrees is proper angle) (25-45 degrees was applied angle) for the latitude of Kermanshah city.

Thermal sensors were employed for measuring the required parameters in the fluid inlet to the collector, a fluid outlet, away from the sun, collector glass shield temperature and the temperature of two points (center and below the absorbent plane) Figure 2.

The applied thermocouple was k-type with an accuracy of 0.1. An 8-channel data logger (PROVA800, Taiwan) was also employed for temperature measurement and recording. The parameters were read by the mentioned data logger every 5 minutes. Data collection was conducted for two types of active fluid. This study lasted for 18 days (9 days for water and 9 days for nanofluid). Data collection was performed every day from 8-19. For each flow rate (0.1, 0.14 and 0.2), data collection was conducted for 3 days. Regarding the previous studies and experiments, as high weight percentage to increase the thermal conductively was not economically justified and highly weighed nanofluids may sediment more with higher particle adhesion (Wu et al., 2009), the weight percentage of 0.2 was considered for the applied nanofluid.

These two types of fluids were tested under the following condition:

1. Water with an angle suitable for the latitude of Kermanshah in three flow rates of 0.1, 0.14 and 0.2 kg/s
2. Bohemite nanofluid with an angle suitable for the latitude of Kermanshah in three flow rates of 0.1, 0.14 and 0.2 kg/s

The calculations were conducted by ANN and SVR methods in Matlab 2013 software.

Figure 1. Flat plate solar collector model, Solar Polar Company, IRAN.

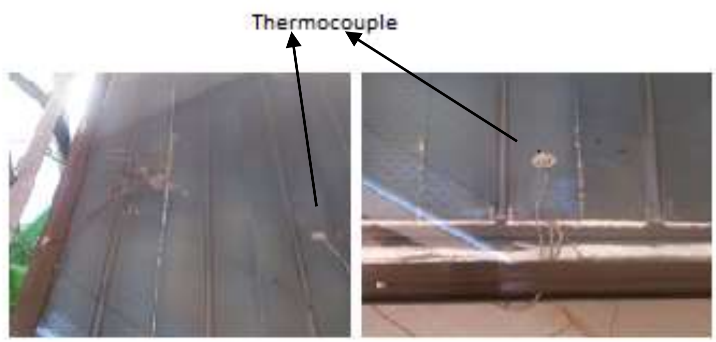

Figure 2. Thermocouple on glass of collector (left), Thermocouple on absorbent plate (right)

RESULTS AND DISCUSSION

Effect of Bohemite Nanofluid on the Collector Outlet Temperature

Temperature variation of the outlet fluid throughout the day was evaluated for different flow rates for the two studied fluids as shown in Figures 3-8. As can be seen, the collector outlet temperature was higher in the case of nanofluid application.

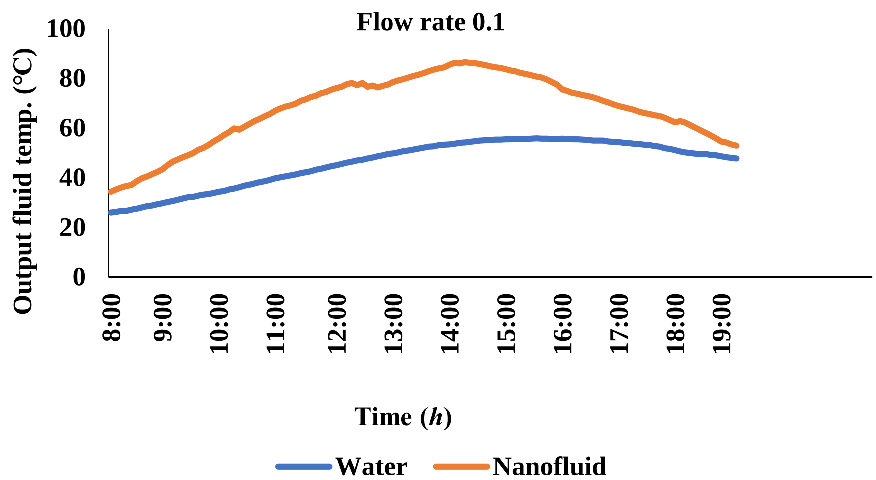

Figure 3. Temperature variation of the outlet fluid in inflow rate 0.1in Jul.16th and 27th with ambient temperature changes of 35 - 41℃.

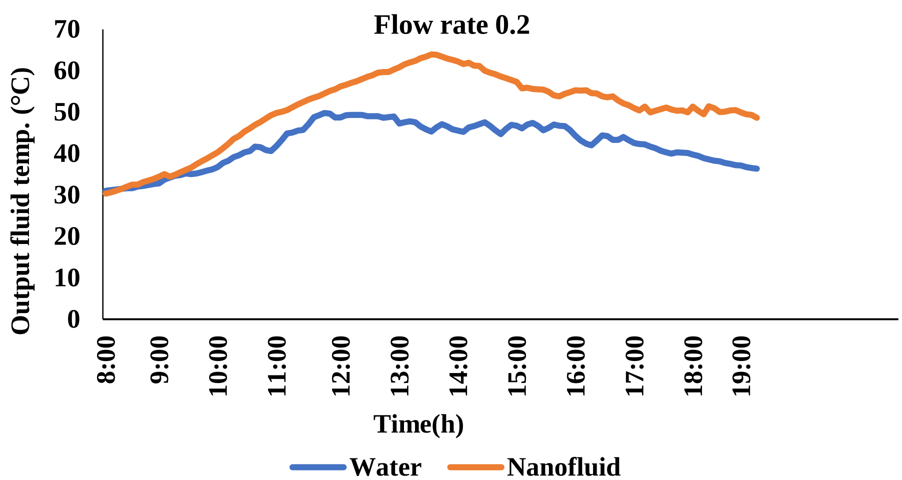

Figure 4. Temperature variation of the outlet fluid in inflow rate 0.2in Jul.22th and Aug.2th with ambient temperature changes of 35 - 41℃.

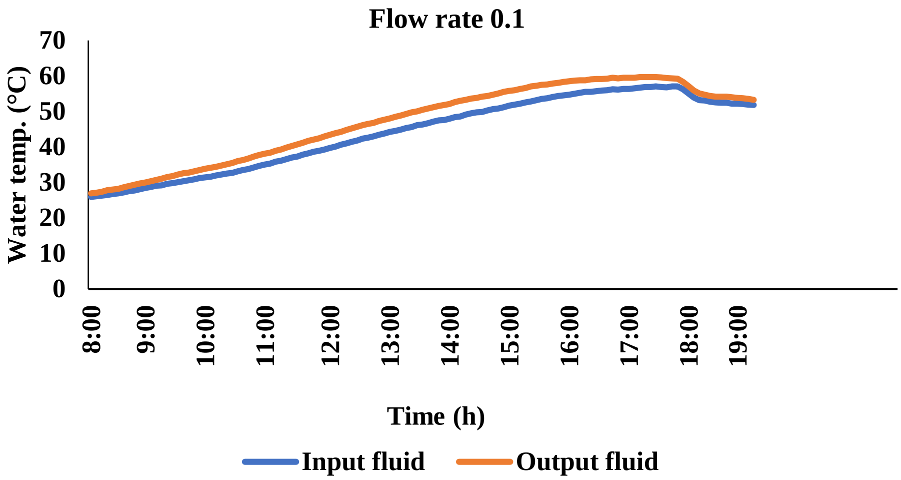

Figure 5. Comparing input and outlet fluid for water in inflow rate 0.1, Jul. 17th.

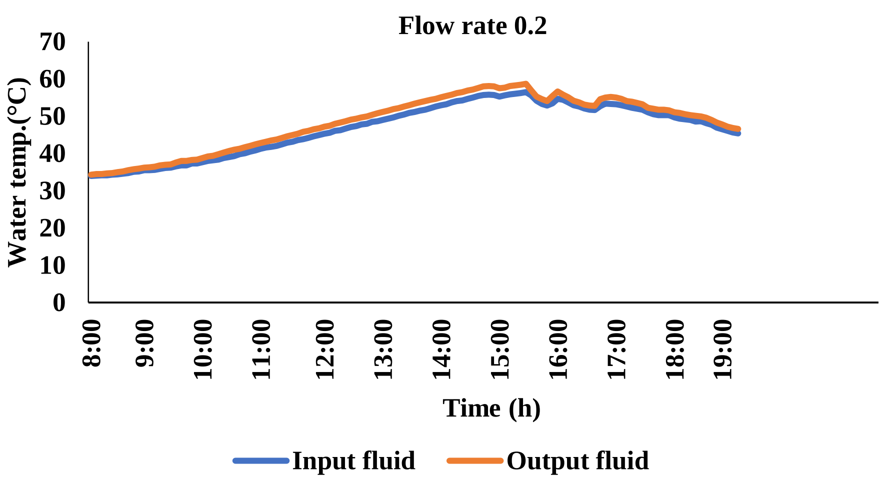

Figure 6. Comparing input and outlet fluid for water in inflow rate 0.2, Jul. 21th.

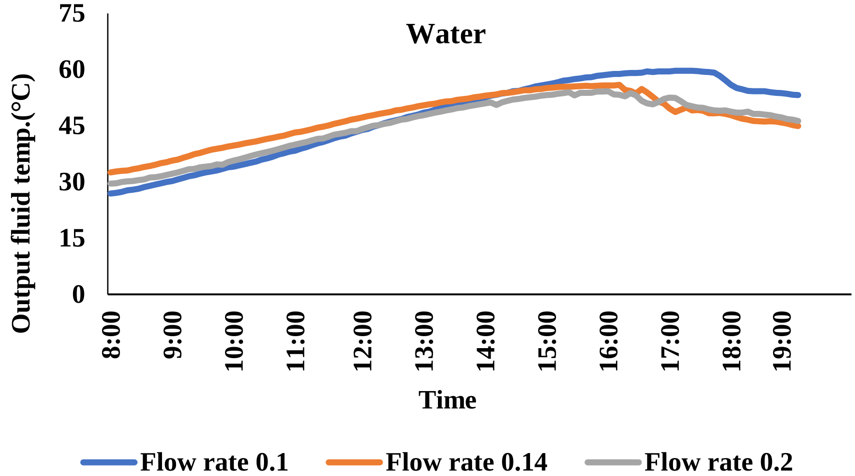

Figure 7. Outlet fluid temp.forwater in various inflow rates in Jul. 17th, 20th& 23thwith ambient temperature changes of 35 - 41℃.

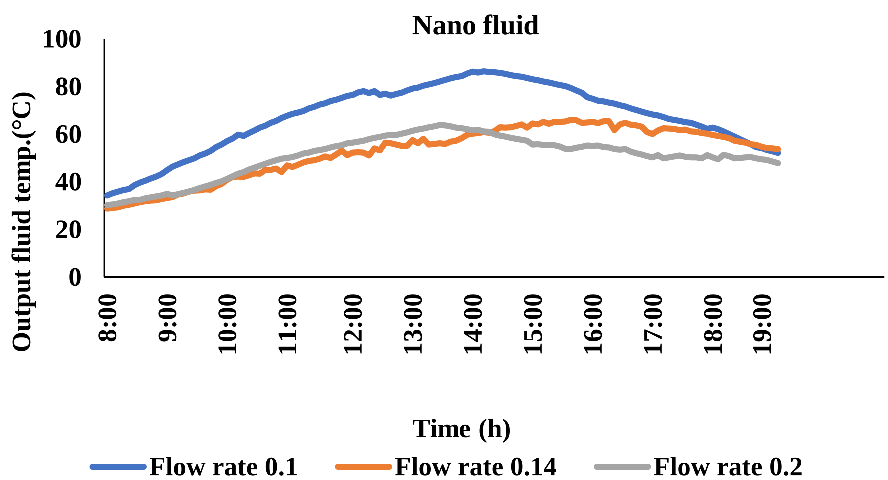

Figure 8. Outlet fluid temperature for nanofluid in various inflow rates in Jul. 27th, 30th& Aug. 2th with ambient temperature changes of 35 - 41℃.

The results indicated that boehmite nanofluid has higher thermal properties compared to water. Therefore, it can be a good alternative for heat transfer mediators. In the case of using the nanofluids, the intensity of heat transfer will be increased by enhancement of the nanofluid thermal conductance coefficient, critical thermal flux, and formation of heat dispersion in fluid flow. As the collector performance is directly affected by the active outlet fluid temperature. Such an increase in the nanofluid temperature will improve the efficiency of the collector. Besides, to increase efficiency, this method is cost-effective. The increase of efficiency without consideration of the economic aspects will be applicable. The results are in line with the reports of Yousefi et al. They conducted a study on AL_2O_3 nanofluid which showed improved efficiency compared to water-ethylene glycol fluid. This indicates the positive impact of the nanofluid on the efficiency of the solar collector (Yousefi et al., 2012).

A prototype direct absorption solar collector having gross area 1.4 m^2 working on the volumetric absorption principle is developed to investigate the effect of using Al_2O_3–H_2O nanofluid as heat transfer fluid at different flow rates. Three flow rates of 1.5, 2 and 2.5l pm were used in this research. The use of nanofluid improves the optical and thermo physical properties that result in an increase in the efficiency of the collector in all cases of using nanofluids in place of water. Collector efficiency enhancement of 8.1% and 4.2% has been observed for 1.5 and 2l pm flow rate of nanofluid respectively. Optimum flow rate of 2.5 and 2l pm towards maximum collector efficiency have also been observed for water and nanofluid respectively (Gupta et al., 2015).

Modeling

When empirical modeling methods do not have the required efficiency for modeling the systems, artificial intelligence can be used to determine the effective relationship between the variables of a system. In this regard, ANN and SVR methods were employed to model the flat plate solar collector outlet fluid temperature.

Results predicted by ANN

As mentioned before, various algorithms have been presented to find the relationship between the target parameter and inputs (training stage) among which Levenberg–Marquardt has been recognized as one of the proper algorithms for predicting and optimizing the solar water heating systems efficiency. For this purpose, a one-layer neural network was trained by all the variables and the efficiency of the solar water heating system was predicted with perceptron structure by minimizing the error in Matlab software. The data were first divided into three groups of training, testing, and validation. The reduction of the applied data for the training will decline the training stage duration. But, even for a small series of data, a large number of probable situations should be considered. In this study, 60%, 20% and 20% of the data derived from properties were used for training, validation, and testing, respectively. In this research feed-forward, ANN was used. To establish a relation between the input layer and hidden layer as well as the hidden layer with the outlet layer, tansig, and purelin functions were employed, respectively. The outlet stimulation function was purelin. One of the major factors in a proper ANN is the proper choice of the independent variable. These variables determine the structure of the designed model and can influence the weight coefficients as well as the final results. To investigate the prediction accuracy of the ANN, the following two structures were used: Figures 9-11.

1- First structure: input layer including TFI, TE, T, FF, F

2- Second structure: input layer includes TG, TC2, TC1, TF1, TE, T, FF, F

For both structures, OFT was considered as the network outlet.

To predict the outlet fluid temperature of the solar water heating system, the input models were investigated based on the effective parameters (Table 1).

Table 1. Input model made based on the effective parameters

Network	Fluid	Parameters
ANN1	Water & nanofluid	OFT= f (F, FF, T, TE, TFI)
ANN2	Water & nanofluid	OFT= f (F, FF, T, TE, TFI, TC1, TC2, TG)

F: type of fluid (water: 1 and nanofluid:2), FF: flow; T: time; TE: ambient temperature; TFI temperature of the input fluid, OFT: the outlet fluid temperature; TC1: absorbent plate 1 temperature; TC_2: absorbent plate 2 temperature and TG: temperature of the glass shield

In the mentioned models, OFT stands for the outlet fluid temperature, the neural system solves the problems through receiving and sending signals. One of the methods for simulation of the neural network efficiency is through data training. The training problem solution is as follows: first, a series of random weights are considered as the initial assumptions; then X input is passed through the mentioned network and the ANN calculated value as the outlet. This value will be then compared with the actual value and the error will be compute, this error will be assigned to the last layer. Then, using a reverse method, this error will be divided on all the weights. In this way, by adding the modulated error to the initial weights, a series of new weights will be obtained. This process will be continued by trial and error until the acceptable value is reached.

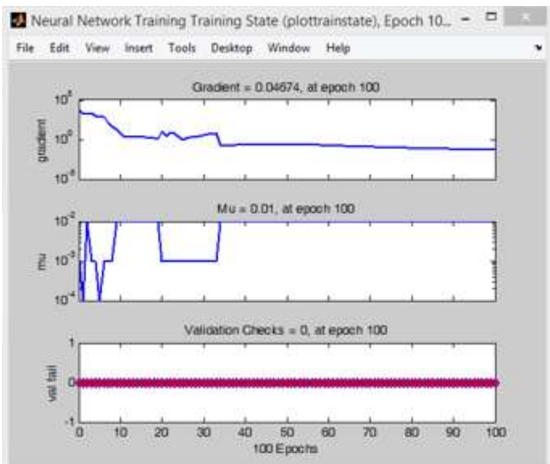

Figure 9. Training state of ANN.

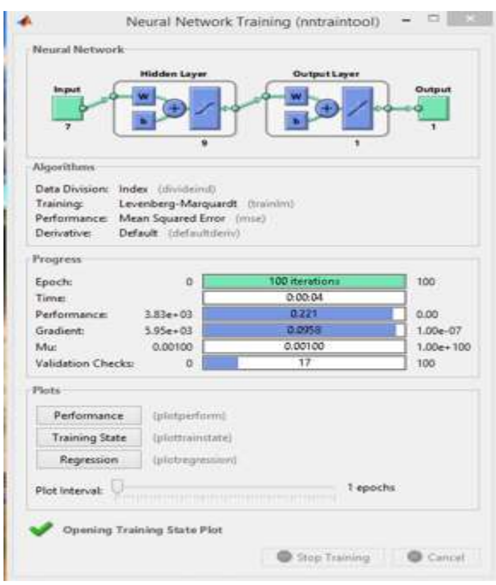

Figure 10. Tools of ANN.

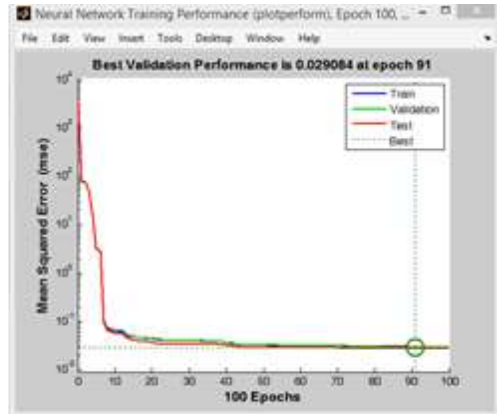

Figure 11. Plot performance of ANN.

Prediction by ANN1

Data in Table 1 were introduced as the input where OFT was considered as the outlet of the artificial intelligence model. OFT predicted by ANN1 are listed in Table 2 for both water and Bohemite nanofluid. Surfactant, Surfactant-Nanofluids, nanofluids as working fluid in the heat pipe collector gives better performance as compared to pure water and performance enhances with an increase in the concentration of the nanofluid (Pise et al., 2016).

The results of the 5-9-1 structure showed the best results with the least mean square error. In this section, networks with various numbers of layers, neurons, and stimuli functions were investigated. To determine the stimuli function and number of neurons, the trial and error method was applied and the condition with lower MSE and higher R was selected as the suitable one. This network had 5 neurons in the input layer and 9 and 1 neurons in the hidden and outlet layers, respectively. The results indicated the prediction accuracy of 99.7619%. This network also had the lowest MSE and the highest correlation coefficient (0.32567 and 0.99886, respectively). The regression of ANN is also presented in Figure12.

Table 2. Prediction results of different ANNs (fluid: boehmite nanofluid and water)

Row	Structure	MSE	R (%)	Prediction accuracy (%)
1	5-3-1	1.1669	0.99571	99.1236
2	5-4-1	1.5756	0.99426	98.8140
3	5-5-1	0.59127	0.99878	99.5544
4	5-6-1	0.68823	0.99756	99.4828
5	5-7-1	0.48000	0.99832	99.6485
6	5-8-1	0.44301	0.99839	99.6710
7	5-9-1	0.32567	0.99886	99.7619
8	5-10-1	0.35134	0.99881	99.7510

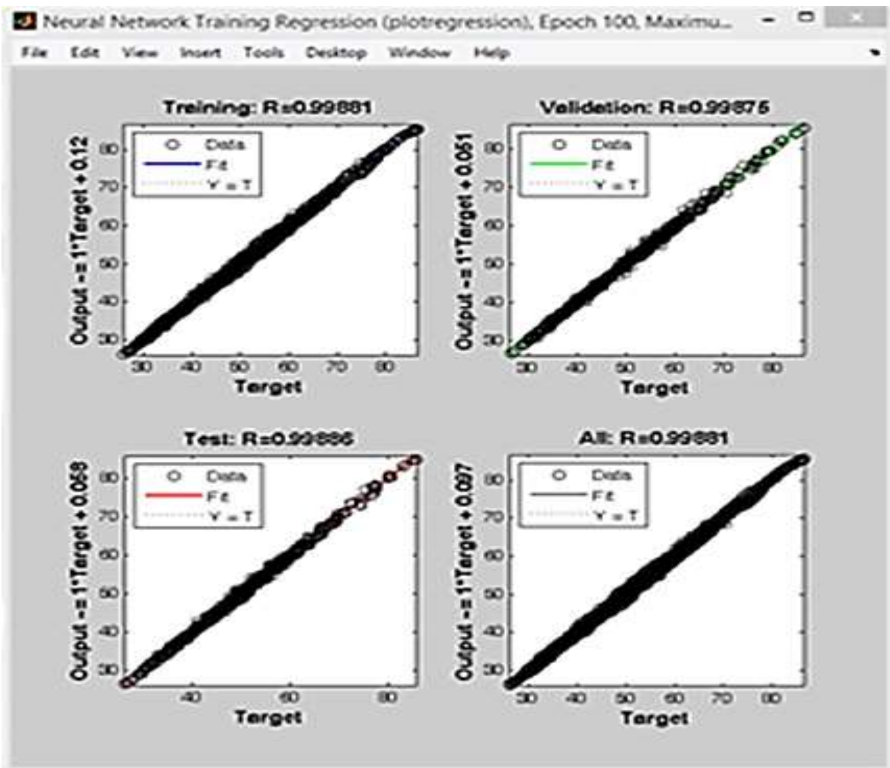

Figure 12. Regression diagram of ANN1

As can be seen, regression coefficients of the training, validation, testing, and total in the optimal network were 0.99881, 0.99875, 0.99886 and 0.99881, respectively. The proximity of the coefficients to No. 1 indicates the high correlation of the outlet network and the real efficiency of the system. Low MSE also reflects that even if the errors are included, the network still can have an accurate prediction which means the high efficiency of the network.

Prediction by ANN2

The prediction results obtained by ANN1 for both fluid types (water and boehmite nanofluid) are listed in Table 3. The mentioned modeling was used to estimate and predict the outlet fluid temperature, in ANN2, the second structure was employed.

An advantage of using nanofluid as a working fluid is that there are mature experiences with building components for these fluids. A commercially available modeling program has been used to model and investigate the performance of the system. The potential and advantages of using nanofluid are discussed. It is found that the thermodynamic efficiencies achievable with nano organic fluid, under optimum conditions, are higher than those obtained from the base fluid (Saadatfar et al., 2014).

Hussein et al. were found that the use of the nanofluid in heat pipe solar collectors can play a significant role in increasing the efficiency of these devices (Hussein et al., 2017).

As Table 3 suggests, the most accurate prediction was obtained by 8-9-1 structure, this network included 4, 6 and one neuron in the input, hidden and outlet layers, respectively. The accuracy of the prediction was 99.8709%. The best model is the one with the highest correlation coefficient and the lowest error. This network has the lowest mean square error and the highest correlation coefficient (0.32678 and 0.99934, respectively). The regression of ANN is also presented in Figure13.

Table 3. Prediction results of different ANNs (boehmite nanofluid and water)

Row	Structure	MSE	R (%)	Prediction accuracy (%)
1	8-3-1	1.2127	0.9954	99.0691
2	8-4-1	1.0669	0.9961	99.2101
3	8-5-1	0.27024	0.9989	99.7919
4	8-6-1	0.61496	0.99789	99.5542
5	8-7-1	0.33979	0.99886	99.7720
6	8-8-1	0.21568	0.99911	99.8328
7	8-9-1	0.32678	0.99934	99.8709
8	8-10-1	0.19582	0.99925	99.8536

Figure13 indicates the relationship between the real temperature of the outlet fluid and the ANN-estimated values. In this Figure, the training, validation and test results are shown.

According to the results, the regression coefficients of the training, validation, testing, and total in the optimal network are 0.99937, 0.99932, 0.99934 and 0.99935, respectively. As suggested by the figure, the proximity of the slope of the passing line to one and low y-intercept indicate the superiority of the model in the estimation of OFT. The nanofluid has a real role in improving the heat pipe solar collectors. It was found that the use of the nanofluid in the heat pipe solar collectors can play a significant role in increasing the efficiency of these devices. (Hussein & et al. 2016)

Yaïci & et al. stated, they employed 3 ANNs with 7, 8 and 9 input variables to predict the efficiency and their model still represented a good accuracy for efficiency prediction (Yaïci et al., 2015).

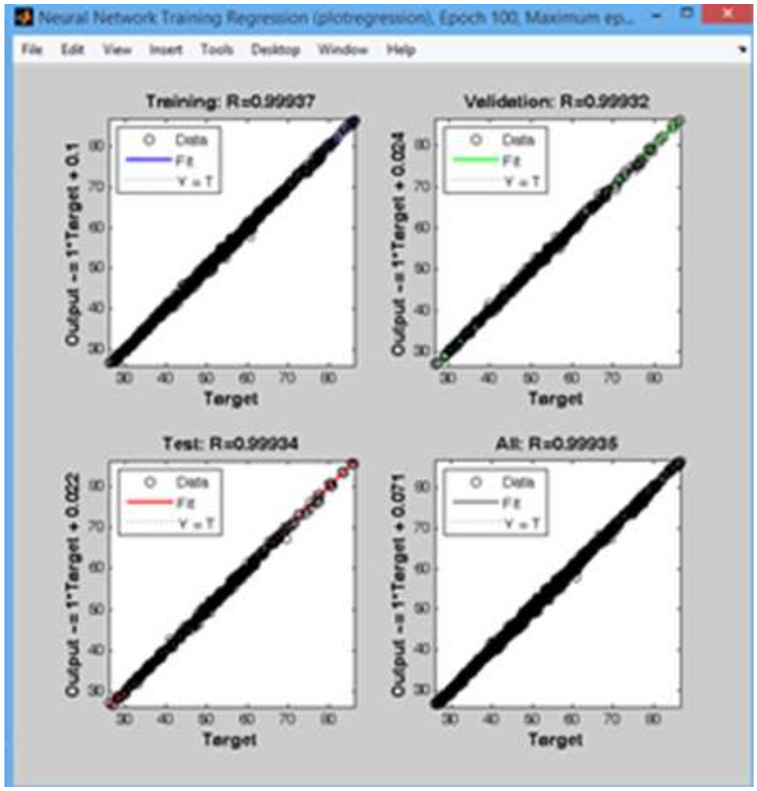

Figure 13. Regression diagram of ANNs

Modeling by SVR method

SVR method estimates a function that can map an input vector to a real value based on the training data. SVR has the properties of maximizing the margin and Kernel method for nonlinear aping. In this method, 70% of the data were employed for training; while the remaining 30% were used for testing the model efficiency. To evaluate the accuracy of the SVR model, two statistical criteria of determination coefficient (R^2) and mean square error (MSE) were used. R^2 value always ranges from 0 to 1; the closer the value to 1, the better the model performance. MSE is a proper index to assess the accuracy of the model. This criterion evaluates the model accuracy based on the difference between the real value and the predicted ones. The closer the MSE value is to 0, the lower the difference will be. Based on the results of the radial Kernel-based developed optimal model (presented in Table 4), R^2 and MSE were calculated as 63.6978 and 281.8210, respectively. For the second structure, the mentioned values were 93.9306 and 15.7420 with the same order. Figures 14 & 15.

The experimental results show that it is possible to achieve enhanced predictive accuracy and capability of generalization via the proposed approach. The calculated root mean square error and correlation coefficient disclosed that SVR_RBF performed well in predicting GSR (global solar radiation) compared with FLR (fuzzy linear regression) (Ramedani et al., 2014).

Table 4. Modeling results using the SVR method

Row	Input	Outlet	R^2	MSE
1	F, FF, T, TE, TFI	OFT	63.6978	281.8210
2	F, FF, T, TE, TFI, TC1, TC2, TG	OFT	93.9306	15.7420

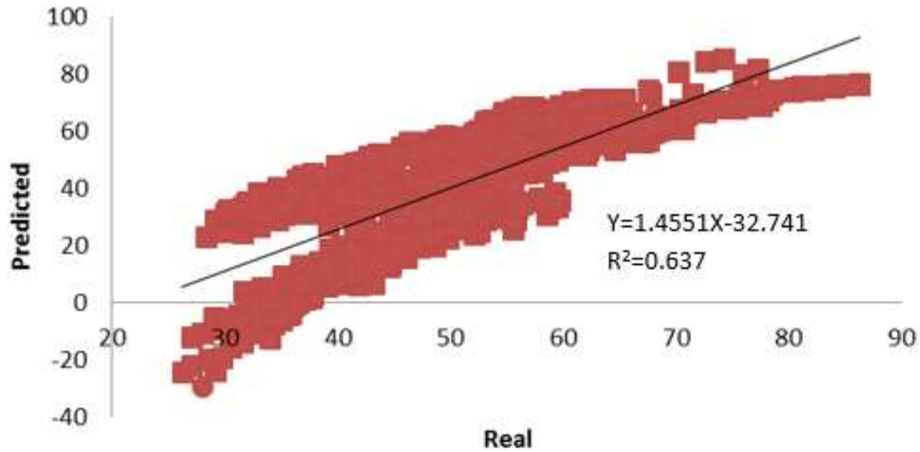

Figure 14. Results of SVR test for inputs of fluid type, flow, time, ambient temperature and input fluid temperature

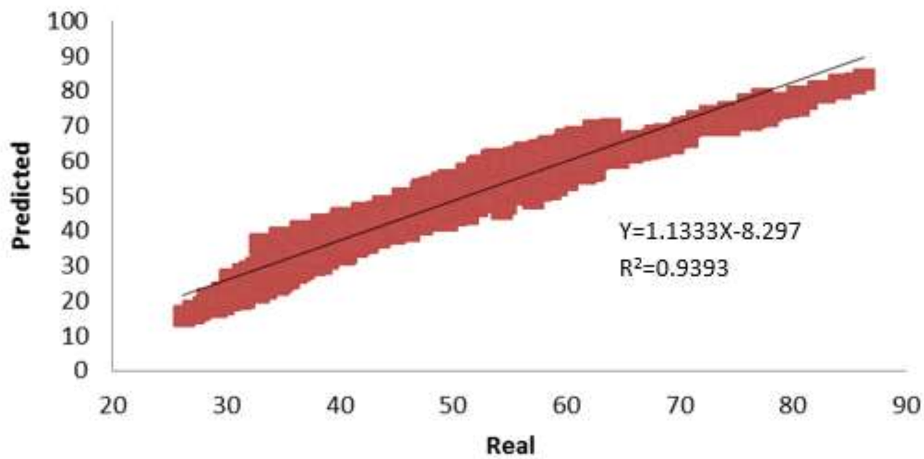

Figure15. Results of SVR test for inputs of fluid type, flow, time, ambient temperature and input fluid temperature, temperature of mid-plate, temperature of the bottom of the plate, and temperature of the glass shield

CONCLUSIONS

This study showed that using the measured parameters as the input of ANN and SVR methods, it is possible to train a model capable of predicting the outlet fluid temperature of a solar water heating system. The modeling results of the two methods showed good agreement with the empirical efficiency. The correlation coefficient and MSE indicated that the trained model with higher inputs can well predict the OFT. A comparison of the ANN results with those of the SVR method showed the superiority of the ANN method. Regarding the results of the present study, it can be said that a single-layer perceptron ANN can serve as a suitable nonlinear method in the prediction of OFT, as shown in Table 5.

A lot of literature is reviewed and summarized to compare results to give a wide overview of the role of the nanofluid in improving the heat pipe solar collectors. In this research, ANN and SVR methods with the effect of Bohemite nanofluid were compared too. Bohemite nanofluid (ALOOH) was dissolved in water and used in a solar heater with a flat plate collector. The solar flat plate collector outlet temperature was higher in this case.

Table 5. Comparison of methods

Methods	Input	Outlet	MSE
SVR	F, FF, T, TE, TFI	OFT	281.8210
SVR	F, FF, T, TE, TFI, TC1, TC2, TG	OFT	15.7420
ANNs	TFI, TE, T, FF, F	OFT	0.32678
ANNs	TG, TC2, TC1, TF1, TE, T, FF, F	OFT	0.32567

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