Optimization of the nonlinear model of neural network training in predicting thermal efficiency of solar concentrator with simulated annealing algorithm

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Abstract

Nowadays, artificial neural networks are widely used to solve large-scale and complex problems. The purpose of this study is to use artificial intelligence techniques such as artificial neural networks and simulated annealing algorithm, to optimize the solar energy system in order to maximize its economic benefits. Here, a new nonlinear computational model has been presented to predict the thermal performance of compound parabolic concentrator (CPC). In this regard, three models of artificial neural network (ANN) including radial-basis function (RBFANN), multi-layer perception (MLPANN) as well as adaptive neuro fuzzy inference system (ANFIS) are used to identify the nonlinear relationship between input and output parameters of the system. The optimal nonlinear structure of the model is determined through the simulated annealing (SA) method. Validation of the proposed models is performed on a CPC. The results show that all the three models are efficient. In particular, statistical analyses show that the ANFIS model is more accurate in the process of predicting thermal efficiency. So, the given models can be effectively applied in practical fields.

Keywords: neural network, nonlinear optimization, simulated annealing algorithm, compound parabolic concentrator, thermal efficiency
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1 Introduction

Integration of renewable energies helps energy systems to reduce energy costs and environmental pollution significantly. In particular, solar energy can be considered as the main source of the energy needed by humans.

Although solar energy is eternal and the most accessible source of energy, it has some undesirable features such as intermittent nature and low density. Designing a centralized solar system is one of the measures to reduce the total cost of the system by increasing outputs through the concentration of sunlight in a small area. Among these concentrators

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is the CPC, which was independently invented by Hinterberger and Winston, and Baranov and Melenukov, in the Socialist Soviet Union [12] and then used in a wide range of practical fields [24, 45].

Determination of thermal efficiency and energy optimization of a concentrator is very important in evaluating its performance. It should be noted that mathematical models of the relevant problem often have nonlinear and complex structures. In the literature, important researches have been conducted to obtain an optimal energy system by changing operational parameters [2, 37, 3].

Most energy systems are modeled and simulated through optimization methods such as ANN [18, 40, 20, 23]. The possibility of finding a relationship between inputs and outputs, simulation and high speed is one of the known benefits of ANN [30]. Although ANN has been considered in many applied researches, it has not been used in modeling CPC systems so far. In this study, three methods of MLPANN, RBFANN and ANFIS are used to model a CPC system. This study is organized as follows. The experimental testing process and data collection are explained in Section 2. Sections 3 and 4 respectively discuss structure of the proposed neural network and its statistical analysis. In Section 5, the implementation of SA algorithm to find the optimal structure of each method is expressed in the modeling of the CPC system. Finally, in Section 6 the performance of MLPANN, RBFANN and ANFIS models in predicting thermal efficiency are compared and the results are reported.

2 Description of testing process and data collection

Schematic of our experimental set is shown in full details by Figure 1. Experimental researches have been conducted on the CPC made with two different liquids of pure water and nanofluid water-SiO_2. The experiment is designed to study the thermal efficiency of CPC as a reference for comparison with the results predicted by ANN. All experiments have been carried out in the city of Semnan, Iran, and in the geographical location latitude $35°14'3,00''$ N and longituide $53°55'8,99''$ E according to the ASHRAE Standard 93-2010 (RA 2014) has been carried out.

Thermal efficiency of CPC is equal to the quotient of the useful energy through a concentrator is delivered to the fluid to the incident radiation, i.e.

$$\eta = \frac{\dot{m}C_p(T_{out} - T_{in})}{AI_t} = \frac{\rho\dot{V}C_p(T_{out} - T_{in})}{AI_t}, \tag{2.1}$$

in which $\dot{m}(\frac{Kg}{s})$ and $\dot{V}(\frac{m^3}{s})$ are mass flow and volumetric flow rate respectively and $C_p(\frac{J}{Kg, K})$ and $\rho(\frac{Kg}{m^3})$ are working heat capacity and fluid density, respectively. As known, the most effective parameters on the thermal efficiency of CPC are input temperature and ambient temperature, fluid mass flow, solar radiation and type of heat transfer fluid (HTF), which are considered as ANN input layer variables.

3 Modeling strategy

In general, modeling is a suitable tool for predicting natural phenomena, which is often presented as conceptual structures and mathematical relations. There are two important features in natural processes that researchers need to deal with: multiplicity of variables and complexity of their relationship. These make the analysis difficult and affect the accuracy of modeling. With these interpretations, ANN and SA algorithm are popularly used among the common modeling methods. The details of our ANN structure and the modeling process are discussed below.

3.1 Artificial neural network

ANN is one of the most efficient soft computing techniques in artificial intelligence systems and uses complex methods to predict output. Nowadays, ANN is an advanced and common approach for modeling various conceptual phenomena in all branches of science and engineering and is a powerful tool for practical analysis. In this method, the model is taught with visual data and then the prediction process begins with appropriate accuracy. In general, ANN, like a function, receives input variables based on the number of neurons belonging to the network input layer and determines the output based on the number of neurons belonging to the network output layer.

3.2 Artificial neural network architectures

ANN architectures commonly used for solar concentrator thermal analysis are MLPANN, RBFANN and ANFIS. Below, we discuss their features in vivid details.
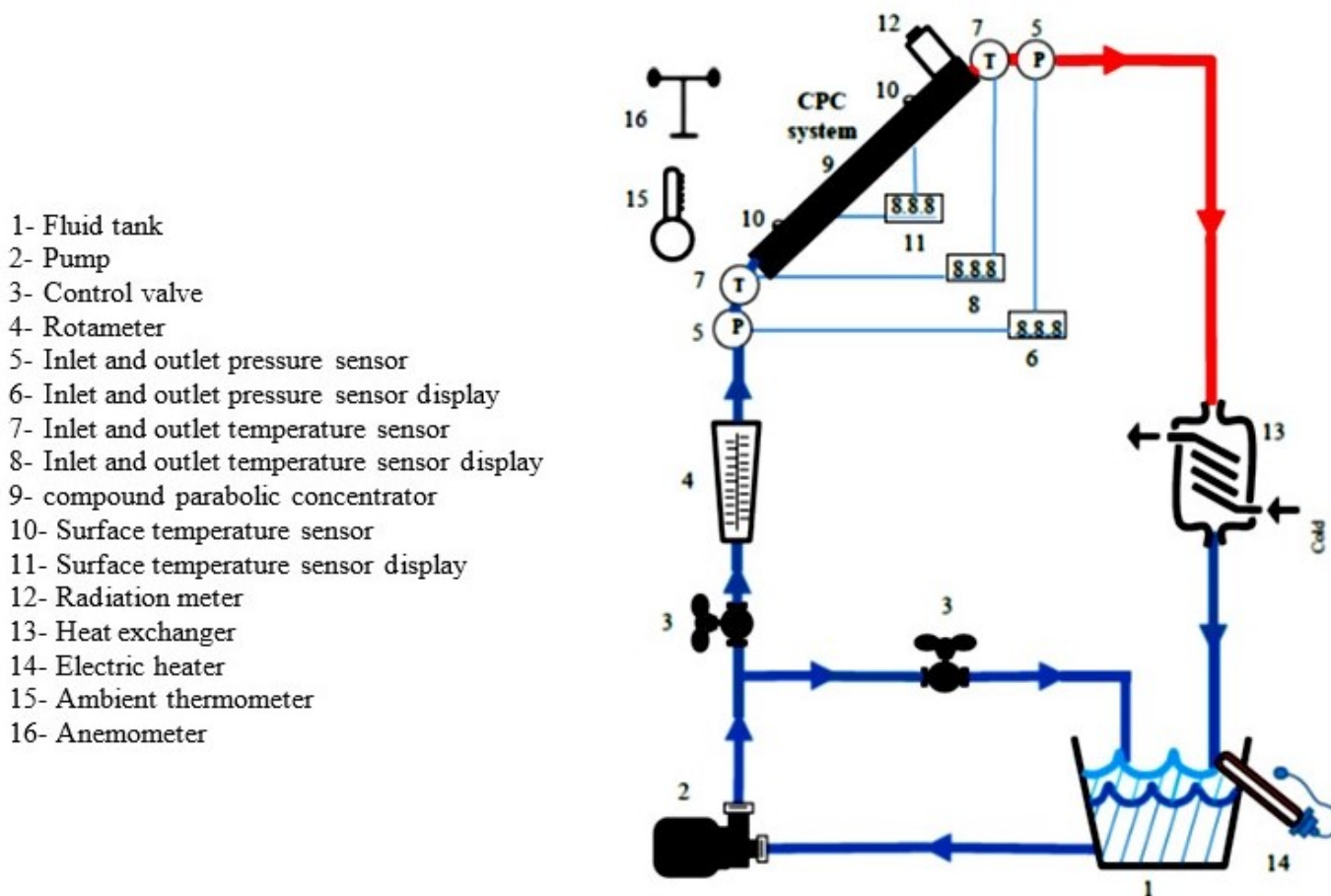
1- Fluid tank
2- Pump
3- Control valve
4- Rotameter
5- Inlet and outlet pressure sensor
6- Inlet and outlet pressure sensor display
7- Inlet and outlet temperature sensor
8- Inlet and outlet temperature sensor display
9- compound parabolic concentrator
10- Surface temperature sensor
11- Surface temperature sensor display
12- Radiation meter
13- Heat exchanger
14- Electric heater
15- Ambient thermometer
16- Anemometer

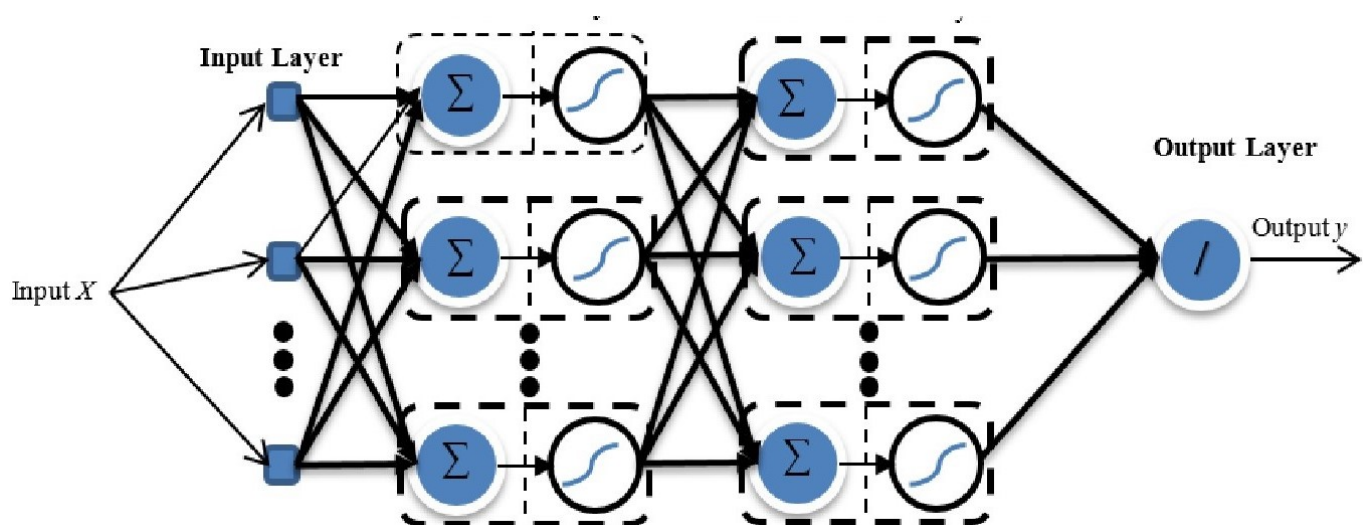Figure 1: Experimental set installed in Semnan University
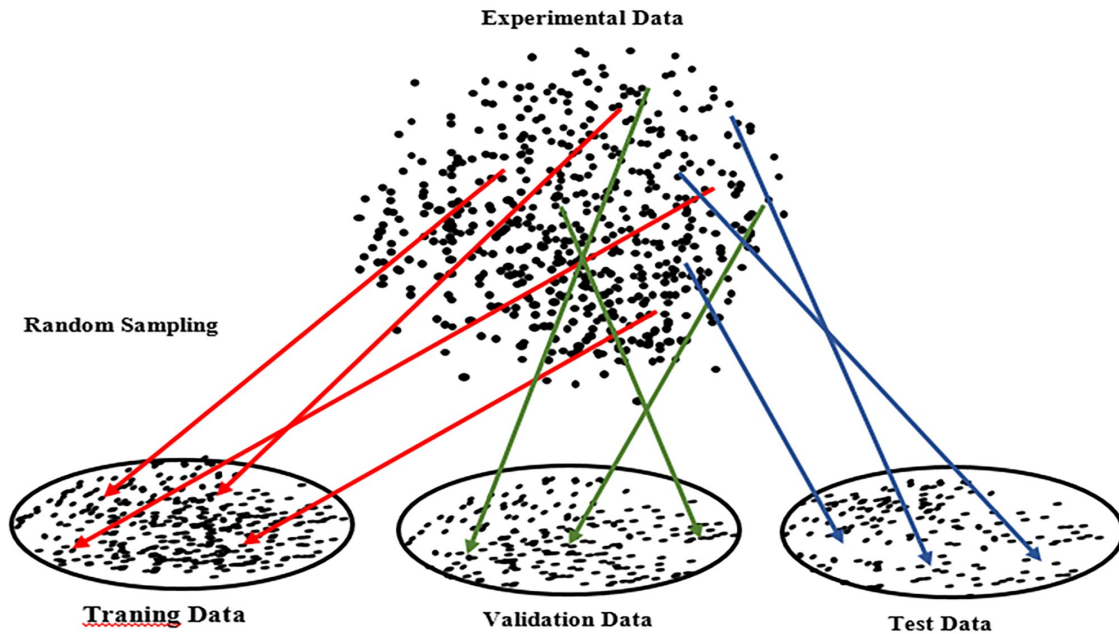

Figure 2: MLPANN Network Structural Diagram

Figure 3: The training data for developing an ANN model

3.2.1 Estimation of thermal efficiency based on Multi-layer perception artificial neural network (ML-PANN)

Multilayer perceptron neural network receives 200 data sets including input temperature, ambient temperature, solar flux, mass flow rate and type of working fluid as input and as a result, it predicts 200 data of the corresponding thermal efficiency as the output of the model. Here, in addition to an input layer and an output layer, MLP has two hidden layers with different types of neurons. In this neural network, educational algorithms bring the trained data to the neural network. The network constantly updates weights and biases until the predicted values match the desired values.

In this model, in the training and evaluation phase, feed-forward back (FFB) propagation algorithm, Levenberg-Marquardt (TRAINLM) method and RMSE functional criterion (root mean square error) are used. In addition, in this neural network model, TANSIG transfer function and LEARNGDM learning function are used [29]. The overall topology to estimate the efficiency of CPC in this neural network model is shown by Figure 2. In this structure, the number of neurons in the input layer is equal to 5, which indicates the number of network inputs. By default, the number of hidden neurons is assumed to be 10. The output layer of the network also has a thermal efficiency neuron. To ensure an effective modeling process, training data for creating an ANN model are usually divided into three parts: training, validation and test data (Figure 3). In the first step (training) the selection of input and output data should be done in such a way that there exists a good relationship between them. The number of input and output variables determines the number of neurons in the input and output layers. The best ANN model is a model in which output data is well-influenced by changing input variables. Therefore, in the first step, based on 70% of the total data, the network is trained to predict the output variables. However, validation is performed in the second stage to increase the accuracy of education. For this purpose, 15% of all data that have not been used in education are used for validation. The last step in the development of the ANN model is the testing phase that is carried out to verify the network. At this point, 15% of the data that has been set aside in the previous two stages are used. If the results are not satisfactory, then the given network will be re-trained. While if the test results are accurate enough, then the training parameters are saved. After the test phase, error analysis is conducted to demonstrate effectiveness of the trained network.

During the training process, the regulator parameters of network models (such as weights, biases, etc.) are systematically updated to match the output data from the neural network to the experimental value of the experimental results. In other words, the error function is attempted to minimize the possible value during training in consecutive repetitions. As mentioned earlier, the purpose of neural network modeling is to build a system that can effectively
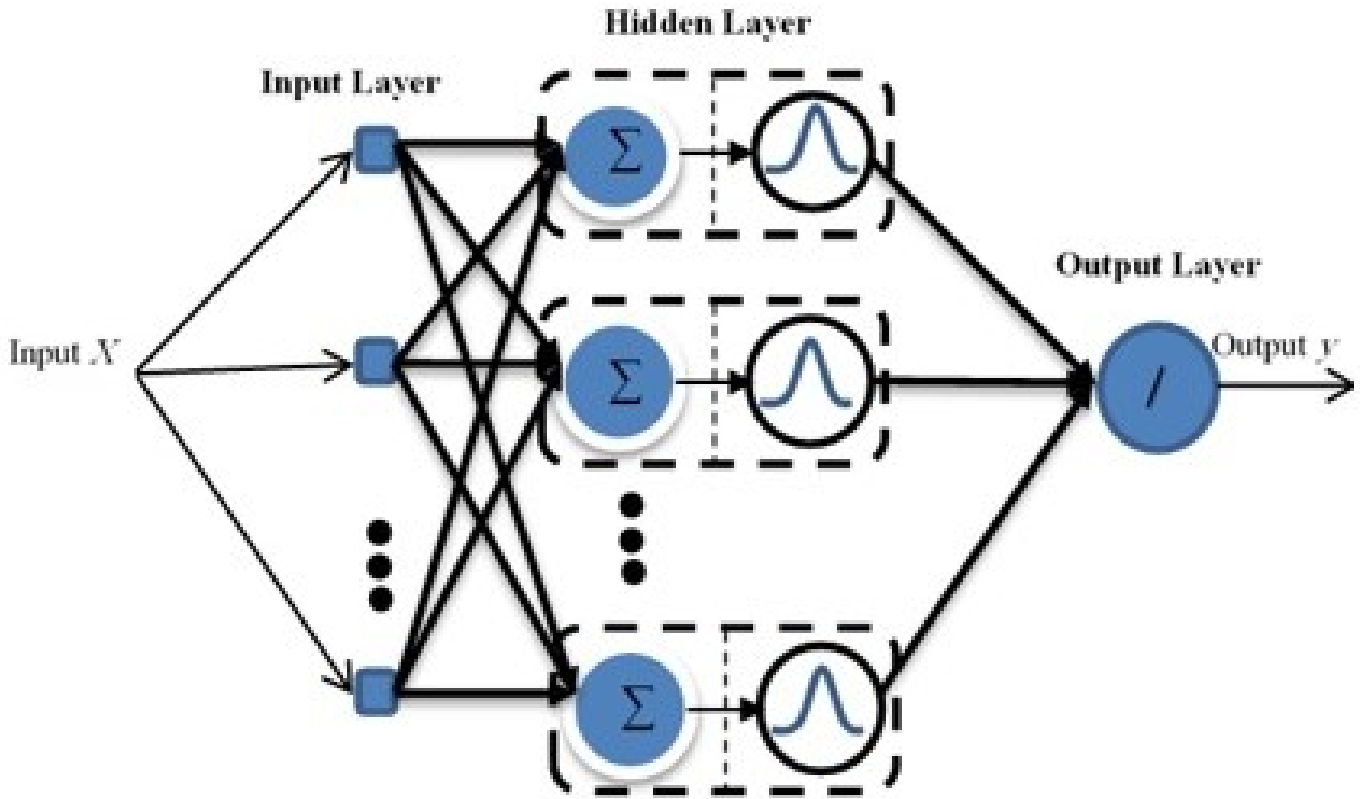
Figure 4: RBFANN model structural diagram

predict output data using input data. When the error function reaches the possible minimum value, neural network training is terminated and from now on, neural network can be used to predict output variables using input variables.

3.2.2 Estimation of thermal efficiency based on Radial-basis function artificial neural network (RB-FANN)

Topology of this type of neural network is shown by Figure 4.The first layer is the input layer and only plays the role of transferring data to the network. The next layer is the unique hidden layer of the network that is composed of a large number of neurons. One of the features of this type of neural network is the rapid learning process, the possibility of network training with the lowest initial data set, determining the optimal size of the network efficiently, and the possibility of escaping from local minima.

3.2.3 Adaptive neuro fuzzy inference system (ANFIS)

ANFIS was firstly proposed in 1993 by Roger [16] through a combination of neural network and fuzzy reasoning. In ANFIS, Sugeno fuzzy sets with two parameters "IF ... THEN" are used as the fuzzy base motor. These parameters play an important role in connecting different fuzzy layers to each other, and by optimizing them, the model is taught. ANFIS is a network structure that is evaluated more effectively than fuzzy systems or single neural network and delivers a more optimal result than both systems [28]. ANFIS structure is composed of 5 layers, each of which has different functions [16, 17] (Figure 5). In this study, the ANFIS has 5 inputs and one output, each layer consisting of neurons with similar function.

Based on the first-order Sugeno fuzzy model, a common rule can be expressed with two fuzzy rules as follows:

Rule 1: If x is A_1 and y is B_1, then, $f_1 = p_1 x + q_1 y + r_1$,

Rule 2: If x is A_2 and y is B_2, then, $f_1 = p_2 x + q_2 y + r_2$,

where x and y are non-fuzzy inputs, A_i and B_i are linguistic labels and f is the output variable. Meanwhile p_i, q_i and r_i are design parameters that are determined during the training process.
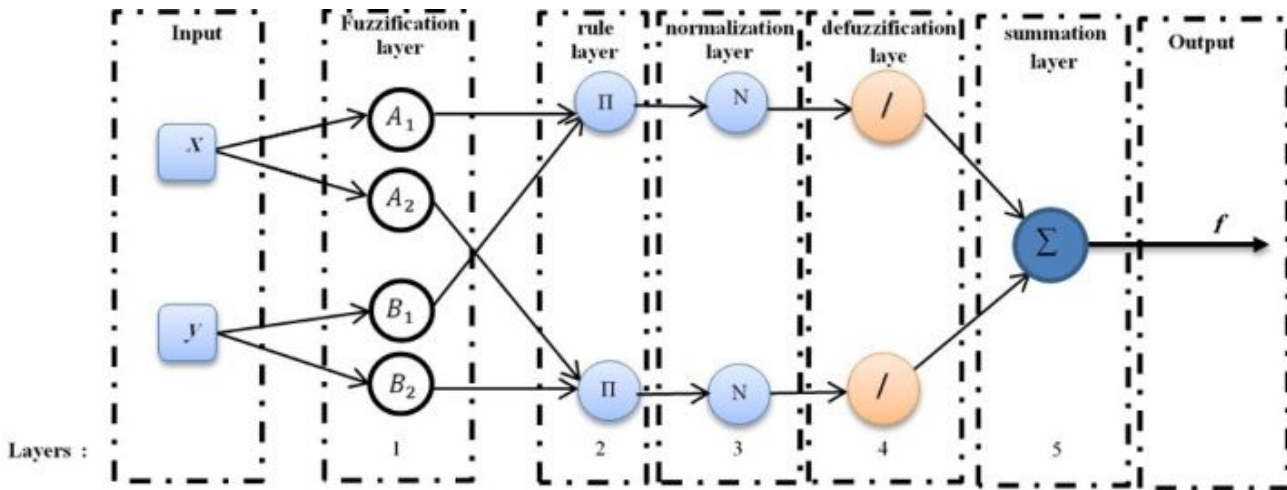
Figure 5: ANFIS Network Structural Diagram

4 Statistical Analysis

Here, MATLAB R2019 programming language has been used to run the neural network program and its models. Different criteria are used to evaluate accuracy of the network and the performance of the proposed model. These criteria include RMSE, allocated variance (VA) and mean absolute percentage error (MAPE) that measures the accuracy of the prediction method and shows how far the data are from the predicted values of the model, while RMSE evaluates the denseness of the data in about the best conditions. MAPE, RMSE and VA are calculated via the following equations:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\eta_i - \hat{\eta}_i)^2}, \tag{4.1}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\eta_i - \hat{\eta}_i}{\eta_i}\right|, \tag{4.2}$$

$$VA = \left[1 - \frac{var(\eta - \hat{\eta})}{var(\eta)}\right], \tag{4.3}$$

where in this η_i is the output value measured or actual, $\hat{\eta}_i$ is the output of the network or the predicted value and n is the number of samples. Another statistical indicator that helps to assess the quality of the fit is regression coefficient or correlation coefficient. Regression coefficient shows how correlated the two groups of measured and predicted data are. If this value is approached to 1, it means that the proposed model performs favorably [39]. The regression coefficient can be determined as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\eta_i - \hat{\eta}_i)^2}{\sum_{i=1}^{n}(\eta_i - \bar{\eta}_i)^2}, \tag{4.4}$$

where $\bar{\eta}_i$ is the average values of η_i. Authentic neural network completes learning process through educational data and confirms the quality of network learning. Finally, by using test data, network validity can be measured in different situations. To develop the network properly, it should be prevented from over-training. RSME values are shown in Figure 6 during the training process. Obviously, with increasing repetition, the amount of error gradually decreases in all three stages of training, validation and testing. As the algorithm progresses at each stage, RSME is recalculated for validation data. The algorithm will not stop until the validation error is reduced. In addition, in this research, network training stops when validation error is decreased in 6 consecutive repetitions (number 6 is the default value in MTLAB software). Increasing the validation check number, although reduces the error of training data, causes the network to be over-fitted and so, the error of test data increases rapidly. Over-fitting is a term commonly used in the neural network and refers to conditions in that due to excessive accuracy and practice, network lowers its error for training data to zero and its prediction range is limited to data close to the training data. In other words, network prediction for data that is not used in the learning process will be accompanied by significant errors. The point where the verification error is minimized is considered as an output. In Figure 6, although the network error for training data is always bearish, the validation error is increasing from 5 repetition onwards. More precisely, since the validation
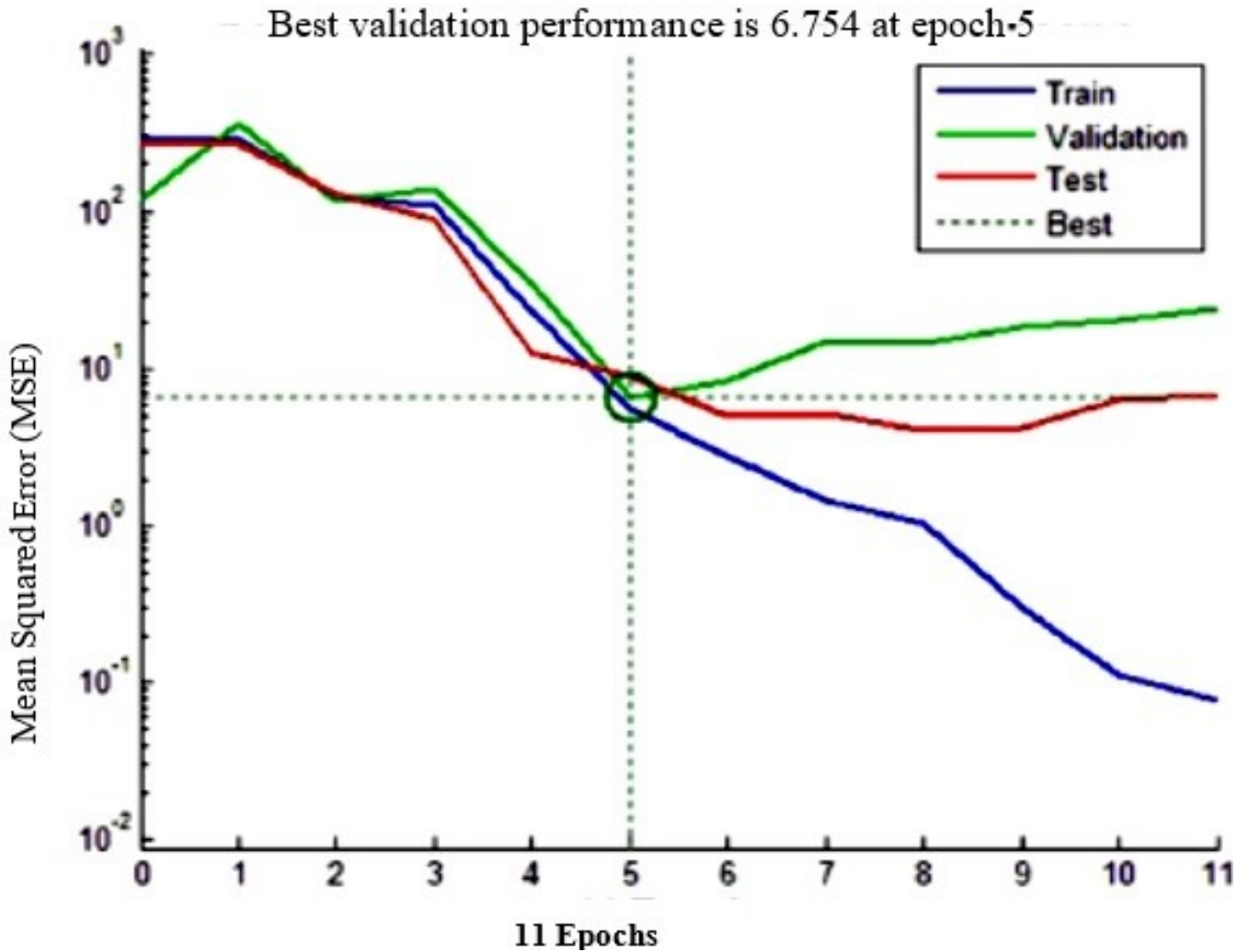
Figure 6: Mean square errors in different repetitions of the training process

error from repetitions 5 to 11 (6 consecutive repetitions) has an increasing trend, so the training algorithm ends and the fifth repetition is considered as the output.

5 Simulated annealing algorithm

As known, metaheuristic algorithms have attracted special attention in developing efficiently robust computational procedures for solving a vast variety of practical decision making problems [26, 47]. They take advantage of the evolutionary approaches to find a global solution, yielding favorable results [4, 19, 21, 31, 32, 33, 35, 41, 42, 43, 44]. These nature-inspired methods are so popular since their softwares can be flexibly reused and also, they can efficiently solve complicated problems even in large scale cases [47, 6, 7, 22, 36].

Among the earliest and most popular metaheuristic techniques of the optimization, there is the SA algorithm. The method origins from the successful annealing process of the materials which involves the cautious control of the cooling schedule [47]. SA is a local search algorithm capable of escaping from local optima by use of random hill-climbing moves in the search process [9, 25, 15]. It is very efficient in practice [15, 34] and well-developed in theory [5, 8, 1].

To provide a detailed description of the SA method [36], at the iteration t of the method a neigh-borhood N_t is defined around the iterate x_t. Then, a neighbor $y \in N_t$ is randomly selected. If y is better than x_t (often in the cost function point of view, i.e: $f(y) < f(x_t)$), then we move to y in the sense that we set $x_{t+1} = y$. However, when x_t is

better than y, we move to y with the probability

$$P_t = e^{-\dfrac{d(x_t, y)}{T}},$$

(5.1)

and stay in x_t otherwise, where $T > 0$ is a constant often called the temperature and $d(x_t, y)$ is a nonnegative function which demonstrates the measure of unfitness of the feasible solution y in contrast to x_t, often de-ned as $d(x_t, y) = f(y) - f(x_t)$.

Temperature T controls the likelihood of cost growth in the sense that for small values of T the cost function unlikely (hardly) increases while for large values of T the distance $d(x_t, y)$ insignificantly affects the value of p_t and any particular transition. In order to guarantee the global convergence with probability one, the temperature needs to be decreased logarithmically with the iteration number t [14, 13], making the process too slow. In practice, the temperature is usually updated by

$$T \leftarrow \lambda T,$$

(5.2)

with a prespecified constant $0 \ll \lambda < 1$

5.1 Selection of neural network structural parameters by SA algorithm

Selecting the optimal value of ANN parameters such as the number of training data, the number of hidden layers, the number of neurons in each hidden layer, the movement factor and determining the learning level are the main processes in ANN modeling [38, 46]. Trial and error method is a technique widely used to optimize ANN configuration. However, this method is time consuming and the resulting configuration may not be optimal. To overcome these defects, ANN approach based on meta-heuristic algorithms was developed to optimize the parameters [27, 10, 11]. In this study, SA which possesses high convergence rate and acceptable accuracy is used to optimize the ANN configuration. In this hybrid model, SA algorithm can help to create closer relationships between inputs and outputs. The resulting optimization parameters are shown in Table 1.

Table 1: Optimized parameters in different neural models

MLPANN	• number of hidden layer{1,3} • number of neuron in each hidden layers:{5,30} • activation function in each hidden layers: {logsig and tansig}
RBFANN	• spread of the Gaussian basis function {1, 10} • number of neurons: {5, 25}
ANFIS	• number of membership function for each inputs {2, 4} • type of input membership functions: {Product of two sigmoidal, Difference between two sigmoidal functions,Gaussian curve, Generalized bell-shaped, P-shaped,Trapezoidal-shaped, Triangular-shaped}

According to the block diagram in Figure 7, the role of SA algorithm is to find the best return value for thermal efficiency prediction process, while ANN (RBFANN, MLPANN and ANFIS) seeks the best mapping function by optimally determining of parameters for predicting thermal efficiency based on SA algorithm. The three criteria of VA, RMSE and R^2 in the neural network are the most important criteria for evaluating the accuracy of the structure created in ANN. Therefore, by selecting a function that can simultaneously determine the best optimal state of these three criteria, the appropriate method for more accurate performance than the predicted structure is created. Therefore, in this study, a hybrid multi-objective optimization method is presented to increase CPC performance To get the best possible result, a nonlinear fitness function called Fit is defined based on the error of the methods as follows:

$$Fit = C_1 \times VA + C_2 \times RMSE - C_3 \times R^2, C_1, C_2, C_3 \in [0, 1],$$

(5.3)

so that $C_1 + C_2 + C_3 = 1$. More precisely,

$$Fit = C_1 \times \left[1 - \frac{var(\eta - \hat{\eta})}{var(\eta)}\right] + C_2 \times \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\eta_i - \hat{\eta}_i)^2} - C_3 \times \left(1 - \frac{\sum_{i=1}^{n}(\eta_i - \hat{\eta}_i)^2}{\sum_{i=1}^{n}(\eta_i - \bar{\eta}_i)^2}\right),$$

(5.4)

Theoretically, it is expected that in order to minimizing the fit function, the complete prediction model have $VA = 1$, $RMSE = 0$ and $R^2 = 1$. The low value of RMSE and the high values of R^2 and VA coefficients indicate the appropriate accuracy of model prediction. By selecting this proportional function, the algorithm is forced to focus on reducing the maximum and minimum error amplitude. To evaluate the performance of the proposed model, using a multi-objective function, we are looking to reduce $RSME$ and increase R^2 and VA coefficients. The optimum parameters of each method are obtained separately. After finding the optimal ANN, the evaluation criteria expressed in the statistical analysis section are used to validate the trained model. From experimental tests on the proposed set (Figure 1) 200 data (in 13 experimental sets) were recorded, while validation was performed with 30 different data.

6 Results and discussion

In this study, the ability of MLPANN, RBFANN and ANFIS to predict thermal efficiency was investigated. As mentioned earlier, these methods are made using five inputs and one output. Firstly, a reciprocal correlation was obtained between observed and predicted values. All the three models showed high accuracy for predicting the output. For more detailed observation, the values of RMSE, VAF, MAPE and R^2 are listed in Table 2. This table shows that despite the high ability of all models, ANFIS and MLPNN offer a more reliable forecasting priority, respectively.

In addition, one-way analysis of variance (ANOVA) and multiple comparisons of three prediction models were performed from the point of view of MLPANN, RBFANN and ANFIS performance. RMSE percentage analysis was statistically significant for p value less than 0.05 (Table 3). In general, it was concluded that to predict thermal efficiency, ANFIS offers less RMSE value compared to the two other methods. A remarkable decrease of RMSE in ANFIS was significant compared to MLPANN ($P < 0.0001$) MLPANN and RBFANN ($P < 0.003$).

Table 2: Performance of each model

Thermal Efficiency	Method	RMSE%	VAF%	MAPE	R^2
Water	MLPANN	0.2621	98.7276	0.4330	0.9980
	RBFANN	0.3560	97.0387	0.4054	0.9972
	ANFIS	0.1975	99.9542	0.3882	0.9983
Water-SiO_2	MLPANN	0.2012	98.927	0.3750	0.9985
	RBFANN	0.3192	98.131	0.4102	0.9981
	ANFIS	0.1838	99.9782	0.3604	0.9988

Table 3: P-Values for comparing the accuracy (in terms of RMSE) for all models

		MLPANN	RBFANN	ANFIS
	MLPANN	$*$	$< 0.003+$	$< 0.0001-$
P-value	RBFANN	$*$	$*$	$< 0.003-$
	ANFIS	$*$	$*$	$*$

Plus/minus signs show that the method in each row has a better/worse performance than the method in corresponding columns After required reviewing the evaluation of ANN performance, the results of the proposed model for each fluid working (experimental data along with predicted data) in Figures 8 and 9 have been presented. These results show that the thermal efficiency of concentrator in different flow rates, input temperature in the range of [45,30] $°C$, and the randomly selected ambient radiation and temperature in the ranges of [1000,700] $W/m2$ and [30,20] $°C$, respectively, have shown good performance. Also, the results emphasize that the predicted data with real data (obtained from empirical experiments) have a suitable compatibility. In addition, according to statistical indicators, it can be concluded that the proposed models have high accuracy.
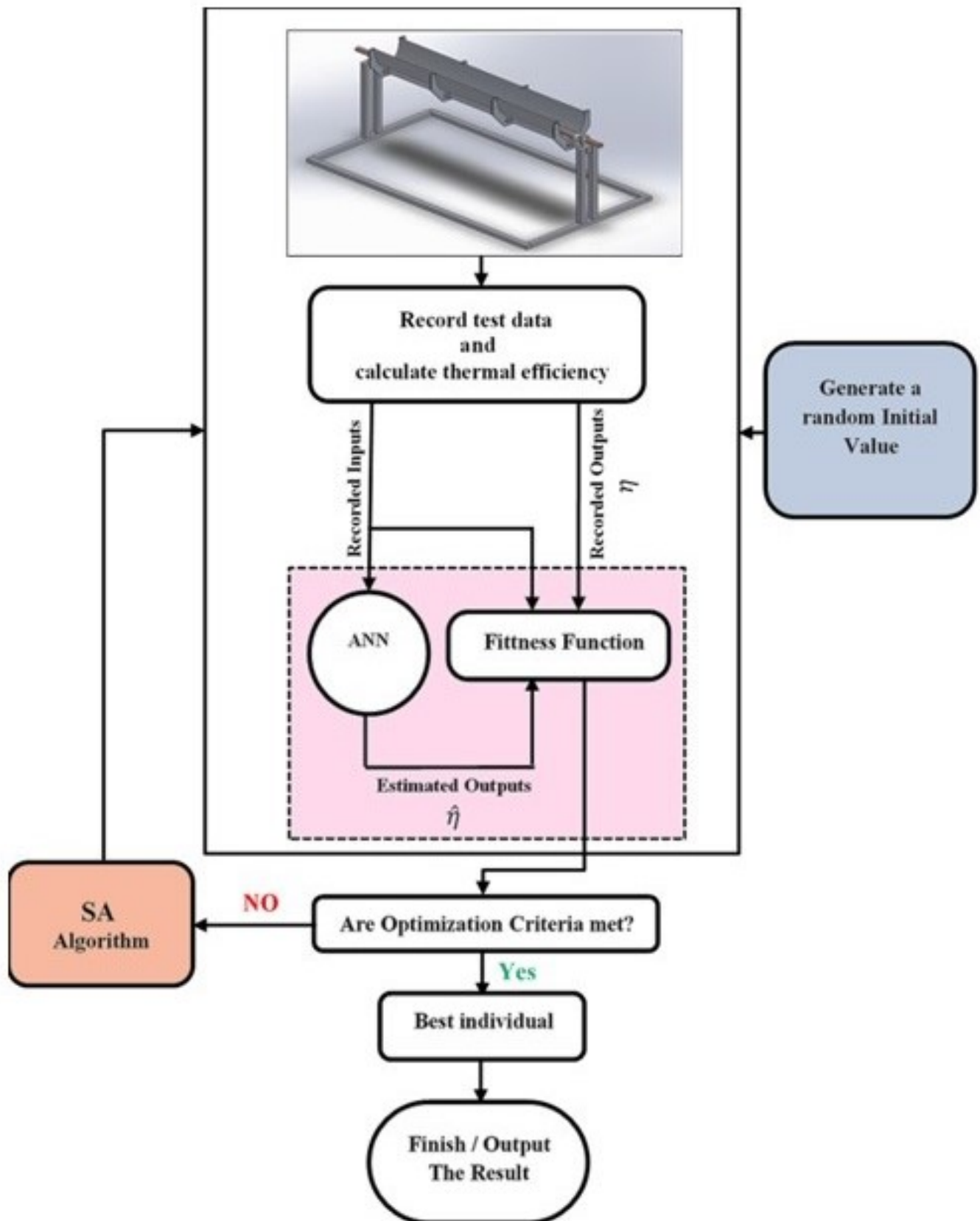
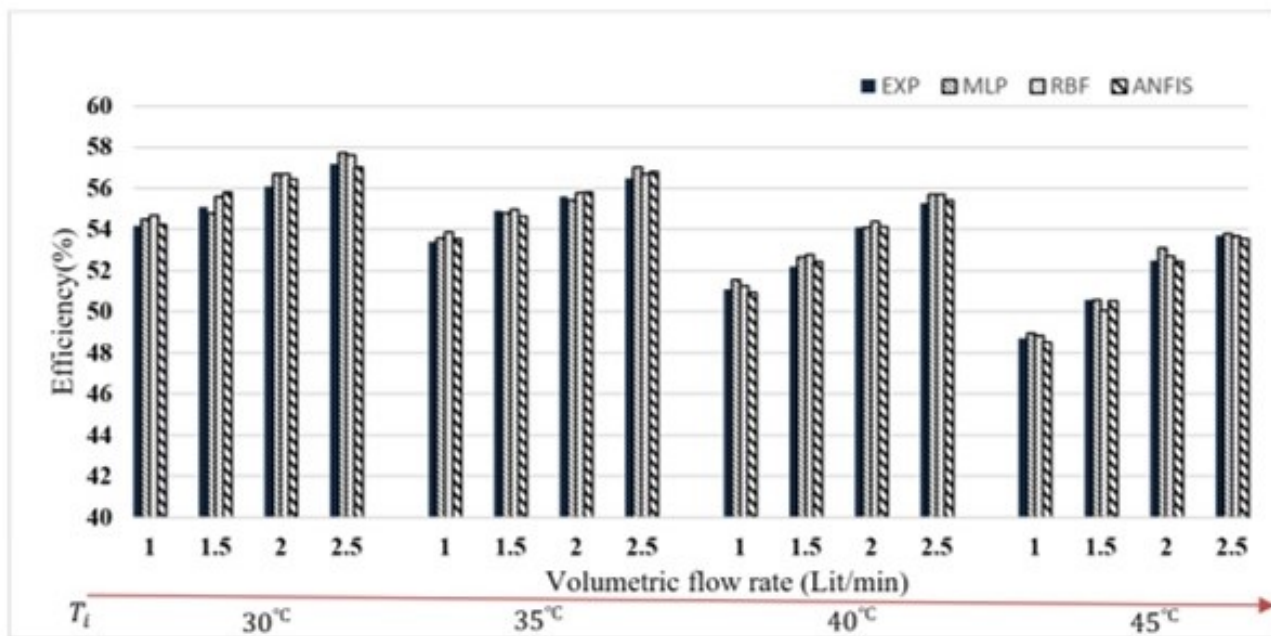Figure 7: Diagram block of the steps and the proposed method

Figure 8: Comparison between predicted and experimental values of the thermal efficiency for water working fluid
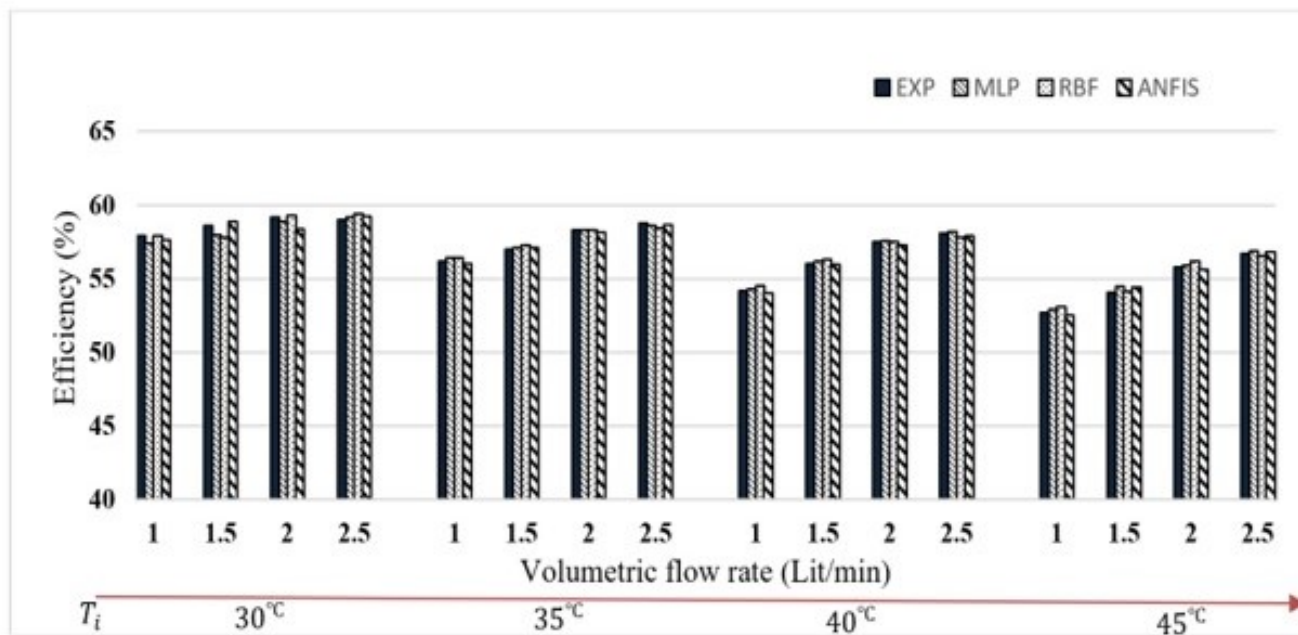

Figure 9: Comparison between predicted and experimental values of the thermal efficiency for water$-SiO_2$ working fluid.

7 Conclusion

In recent years, neural networks and fuzzy inference systems have been widely used to develop prediction models. In this study, MLPANN, RBFANN and ANFIS neural networks combined with SA meta-heuristic algorithm were used to model a CPC system under different conditions. In general, the results showed that these methods are able to estimate thermal efficiency with high accuracy and in addition, input parameters (climatic conditions, radiant flux and input temperature) contain important information about CPC modeling. In addition, it was found that ANFIS in predicting thermal efficiency has better performance than the other two models. In addition, MLPANN model performance has been better than RBFANN model. Therefore, the results of this study showed that all the three models of ANFIS, MLPANN and RBFANN are well suited for modeling nanofluid applications in solar systems. The main purpose and motivation of this study was to find a simulated model suitable for the CPC system that would help engineers achieve an optimal design. The results of this study have drawn effective strategies to achieve this goal.

Limited research has been reported using the ANN approach combined with the SA metaheuristic method. Hence, extending the suitability of ANN in combination with SA is essential for a wide range of solar applications. This study showed that the values predicted by ANN, especially with the SA algorithm, can be used accurately to predict the performance of solar collecting systems, working with nanofluids. Therefore, instead of predicting the collector efficiency for different types of mass flows and different working fluids, faster and simpler solutions are obtained using ANN instead of limited experimental data without the need for experimental work. This structure based on ANN model can be used as a suitable alternative method in different systems to determine the thermal performance of solar collectors, heat exchangers, the behavior of different nanoparticles and determine their thermal properties, optimization and forecasting of various functions of thermal power plants and etc.

The proposed model is a general model and can be used to analyze different collector systems. Among the tasks that can be suggested in the future of this study is the exergy analysis of solar collectors using ANN models with a very good future range for optimizing the size, geometry, type of working fluid and cost of solar collectors. It is also possible to improve the results compared to the SA algorithm by combining other ANN models with other metaheuristic algorithms.

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