3-1-2020

Comparative and performative investigation of various data-based and conventional theoretical methods for modelling heat pipe solar collectors

Abdellah Shafieian
Edith Cowan University

Hossein Parastvand
Edith Cowan University

Mehdi Khiadani
Edith Cowan University

10.1016/j.solener.2020.01.056

This paper has been published as Shafieian, A., Parastvand, H., & Khiadani, M. (2020). Comparative and performative investigation of various data-based and conventional theoretical methods for modelling heat pipe solar collectors. Solar Energy, 198, 212-223. doi:10.1016/j.solener.2020.01.056

Comparative and performative investigation of various data-based and conventional theoretical methods for modelling heat pipe solar collectors

Abdellah Shafieian, PhD Candidate, School of Engineering, Edith Cowan University, 270 Joondalup Drive, Joondalup, Perth, WA 6027, Australia

Email: a.shafieiandastjerdi@ecu.edu.au

Hossein Parastvand, Research Assistant, School of Engineering, Edith Cowan University, 270 Joondalup Drive, Joondalup, Perth, WA 6027, Australia

Email: h.parastvand@ecu.edu.au

Mehdi Khiadani, Associate Professor, School of Engineering, Edith Cowan University, 270 Joondalup Drive, Joondalup, Perth, WA 6027, Australia.

Tel.: +61 8 6304 5825; fax: +61 8 6304 5811.

Email: m.khiadani@ecu.edu.au (author for correspondence)

Abstract

Solar collector, as the key component of any solar system, has always been the focal point of research in the field of solar energy. Based on the literature, data-based methods, which have been proven to be promising in accurate modelling of solar collectors, have not been used for modelling heat pipe solar collectors (HPSCs). At the same time, accurate equations relating the thermal efficiency of solar collectors to the operational and climatic conditions have not been obtained for HPSCs. Therefore, in this study, various data-based and energy balance-based modelling methods were proposed, and based on different accuracy criteria, their precisions were compared in predicting the performance of HPSCs. First, an experimental rig was manufactured and the operational data of the system was recorded throughout a year. The recorded experimental data was used to train and validate various modelling approaches. Then, the accuracies of the proposed models were analysed and assessed. The evaluated models included Artificial Neural Network (ANN), Thermal Resistance Network (TRN), Artificial Neuro Fuzzy Inference System (ANFIS), and Fuzzy methods. Among different modelling approaches, ANN had the best performance which was followed by the ANFIS and TRN methods. The Fuzzy method was not recommended due to its poor accuracy. In addition, the optimum equations relating the outlet temperature of HPSCs to the operational conditions of the solar water heating systems as well as the climatic conditions were obtained and verified.

Keywords: Solar water heating; Data-based modelling; Heat pipe solar collector; Energy balance modelling

1. Introduction

Theoretical modelling has played an important role in the design, performance assessment, and efficiency improvement of energy systems. Modelling not only increases the ability to analyse energy systems under different conditions, but also provides great opportunities for new designs and optimisation (Yılmaz and Mwesigye, 2018). In addition, the experimental analysis requires cost, time, and manpower. On the other hand, modelling is cost effective, quick, and requires less manpower (Liu et al., 2017). That is why both the conventional and data-based methods have been widely used in modelling energy systems.

For instance, ANFIS and ANN, as data-based methods, were successfully used by Esen et al. to simulate the performance of a ground-coupled heat pump in Turkey (Esen et al., 2008c, d). The results, which were obtained from both methods, were compared based on several comparative parameters (Esen et al., 2008a). Statistical weighted pre-processing was then used to enhance the performance of ANFIS and ANN methods in predicting the daily performance of the system (Esen et al., 2008b, e). Bui et al. (Bui et al., 2020) modified the ANN method and proposed a new hybrid technique to predict the energy consumption of buildings and emphasised its importance in early stages of the energy-efficient designs in buildings. Hydrogen production systems (Yilmaz et al., 2019), street lighting systems (Mohandas et al., 2019), and wind energy systems (Marugán et al., 2018) are other samples energy systems in which data-based methods have been applied.

Similarly, a great share of studies in the field of solar systems has been focused on the theoretical performance prediction of different types of solar collectors. The most important element of any solar system is its solar collector which acts as a heat exchanger to convert solar radiation into the working fluid’s internal energy (Kalogirou, 2004). Solar collectors can be classified into three major groups: Flat Plate Solar Collectors (FPSC), Evacuated Tube Solar

Collectors (ETSC), and Heat Pipe Solar Collectors (HPSC) (Daghigh and Shafieian, 2016). Different types of solar collectors in various configurations have been applied in many applications such as water heating (Esen and Esen, 2005), air heating (Kumar and Rosen, 2011), drying (El-Sebaii and Shalaby, 2012), desalination (Shafieian and Khiadani, 2019), and solar cooking (Esen, 2004).

FPSCs are known for their cheap price and simple structure (Shafieian et al., 2019b); however, they have shown significant drawbacks such as high hydraulic resistances, high thermal losses, and dependency on sun trackers for better efficiency (Sabiha et al., 2015a; Sabiha et al., 2015b). Both conventional and data-based methods have been used in previous studies for modelling FPSCs. Carmona and Palacio (Carmona and Palacio, 2019) used energy balance equations for thermal modelling of a FPSC with latent heat storage which was resulted in maximum error of 4.62% between the modelling predictions and the experimental data. Farajzadeh et al. (Farajzadeh et al., 2018) applied energy balance equations to explore the effect of using nanofluids on thermal efficiency improvement of FPSCs, and 11% difference was recorded between the theoretical predictions and the experimental data.

Kalani et al. (Kalani et al., 2017) applied radial-basis function and multi-layer perception ANN methods along with the ANFIS technique to model a flat plate PV/T solar collector. The structure of the developed networks in this study was optimised using Particle Swarm Optimization technique. Based on the obtained results, the ANFIS methods was recognised as the most accurate method for modelling flat plate PV/T solar collectors. Mohanty et al. (Mohanty et al., 2017) compared different types of data-based methods for estimating the solar radiation as well as the thermal efficiency of FPSCs and proposed these methods as promising techniques in modelling solar systems. Caner et al. (Caner et al., 2011) compared the performance of two types of FPSCs by designing an ANN model based on the collected experimental data. Esen et al. (Esen et al., 2009) used ANN and wavelet neural network (WNN)

methods to investigate the performance of a novel flat plate solar air heater. The results, which were assessed based on several statistical validation parameters, showed the capability of the WNN model in accurate modelling of solar air heaters.

Diez et al. (Diez et al., 2019) compared the performance of ANN method in predicting the outlet temperature of flat plate solar collectors with two conventional methods (i.e. international standard ISO 9806 and Hottel-Whillier-Bliss). The accuracies of the predicted data, which were obtained for different solar working fluid mass flow rates, were analysed in detail and showed the advantages of ANN over other methods. Fischer et al. (Fischer et al., 2012) proposed the usage of Artificial Neural Network (ANN) models, instead of using the conventional European Standard EN 12975-2, for analysing the performance of FPSCs. They concluded that the results obtained from ANN model showed better agreement with the experimental data compared to the results obtained from EN 12975-2 Standard. Both ANN and ANFIS methods were applied in a study by Esen et al. (Esen et al., 2017) to simulate a flat plate solar ground source heat pump system. ANFIS was recognised as a more suitable method in predicting the performance of the system.

The main aim of proposing the second group of solar collectors (i.e. ETSCs) was decreasing the thermal losses and enhancing the thermal efficiency especially in cold climatic conditions (Sabiha et al., 2015b); however, the possibility of overheating has been mentioned as their major drawback (Shafieian et al., 2018). Just like FPSCs, both conventional and data-based methods have been widely used in previous studies for modelling ETSCs. Naik et al. (Naik et al., 2016) applied Thermal Resistance Network (TRN) method to investigate the effects of using different working fluids on the performance of U Type ETSCs, and a maximum error of 8.36% was observed between the theoretical and experimental data.

Saikia et al. (Saikia et al., 2019) investigated the effects of vacuum deterioration on the thermal efficiency of ETSCs by developing a steady state one-dimensional mathematical model which showed noticeable deviations from the experimental efficiency curves in some cases. Liu et al. (Liu et al., 2017) introduced a new technique based on data-based methods for thermal evaluation of water-in-glass ETSCs. They concluded that the proposed model could be extended to be used in the design of solar energy systems. In another study, the heat loss coefficients along with the heat collection rate of water-in-glass ETSCs were determined using the ANN technique (Liu et al., 2015).

HPSCs were proposed to address the challenges of the previous two types of solar collectors. High heat removal from the absorber, low thermal resistance, higher heat transfer capability, and low possibility of overheating are main advantages of HPSCs. These advantages are the main reasons for researchers' attraction towards HPSCs especially in the last few years. A significant share of these investigations have been focused on modelling and optimisation due to recent developments in computing power and processes (Shafieian et al., 2019b).

Ersoz (Ersöz, 2016) developed a steady state energy balance-based theoretical model to analyse the performance of six solar working fluids in a HPSC under climatic conditions of Turkey. A10% maximum relative error was observed between the theoretical results and the experimental data. The influences of climatic conditions, structural parameters, and operational inputs on the thermal efficiency of a new type of microchannel HPSC were investigated by Diallo et al. (Diallo et al., 2019) using a steady theoretical model. In another theoretical study, Chew et al. (Chow et al., 2011) compared the performance of ETSCs and HPSCs in Hong Kong and concluded that the annual thermal performance of the latter collector was higher than the former one.

Elsheniti et al. (Elsheniti et al., 2019) simulated the heat transfer processes of a HPSC using the TRN method without and with considering the collector's thermal mass, which resulted in maximum and relative errors of respectively 12.5% and 4.4% between theoretical and experimental data. Shafieian et al. (Shafieian et al., 2019c) applied TRN method for determining the optimal absorbing area of a HPSC aimed to be applied in a solar domestic water heating system in Australia. They concluded that 25 is the optimum number of heat pipes for a collector which is intended to be operated under climatic conditions of Australia. In a theoretical and experimental study, Taoufik et al. (Taoufik et al., 2013) considered various physical parameters of a HPSC (e.g., absorber plate material, spacing gap, and absorber plate emissivity) and investigated their effects on the thermal efficiency of the solar collector. Their proposed model was the combination of energy balance equations and TRN method. Among the considered working fluids, acetone showed the best thermal performance.

The literature review reveals that even though the data-based methods have been proven to be promising and more accurate in modelling FPSCs and ETSCs, all the efforts in the field of HPSCs have been focused on conventional methods. In other words, to the best of authors' knowledge, a study considering various data-based techniques to simulate the performance of HPSCs has not been reported in the literature. In addition, while accurate equations relating the output parameters of a solar collector to the operational and climatic conditions in a solar water heating system are well-studied and established for FPSCs and ETSCs, such equations are completely under-researched for HPSCs.

Based on the mentioned research gaps, the objectives of this study are (i) developing various data-based and conventional theoretical methods and comparing their accuracies in predicting the performance of HPSCs in solar water heating systems and (ii) obtaining accurate equations to describe the complex non-linear relationship between the outlet temperature of HPSCs and

the operational conditions of the solar water heating system as well as the climatic conditions under which the system operates.

First, an experimental rig was manufactured (Shafieian et al., 2019d), and then the operational data of the system was recorded throughout a year. The annual experimental data in this study was firstly required for training and validating different modelling approaches and secondly for evaluating their precisions. Then, several models based on Artificial Neural Network (ANN), Thermal Resistance Network (TRN), Artificial Neuro Fuzzy Inference System (ANFIS), and Fuzzy methods were developed and compared. In addition, accurate equations relating the outlet temperature of HPSCs to the operational conditions of the solar water heating system as well as climatic data were obtained and verified.

2. Experimental setup and instrumentation

2.1. Experimental rig

Figures 1 and 2 respectively depict the schematic design of the heat pipe solar water heating (HPSWH) system and the manufactured experimental rig which was tested throughout a year under climatic conditions of Western Australia. The main components of a HPSWH system include a HPSC, a water storage tank, a control unit, pipes and fittings, a pump, and several valves (Fig. 1). The solar radiation that passes the vacuum glass, is absorbed and transferred to the solar working fluid using heat pipes. The pump, which is used in the solar loop, circulates the solar working fluid through the manifold section of HPSC and the copper coil inside the storage tank. The heated solar working fluid transfers its thermal energy to the water inside the storage tank. Based on the hot water consumption pattern (Shafieian et al., 2019c), the water is extracted at the required temperature (i.e. usually 60 °C) and will be replaced with cold tap water.

For further information regarding the components, working principles, control, and operational parameters of the system, the readers are referred to the authors' previous publications (Shafieian et al., 2018, 2019a). The sizes, dimensions, manufacturing process, test conditions, measurement, and uncertainty analysis of the solar system can be found in authors' previous publication (Shafieian et al., 2019d).

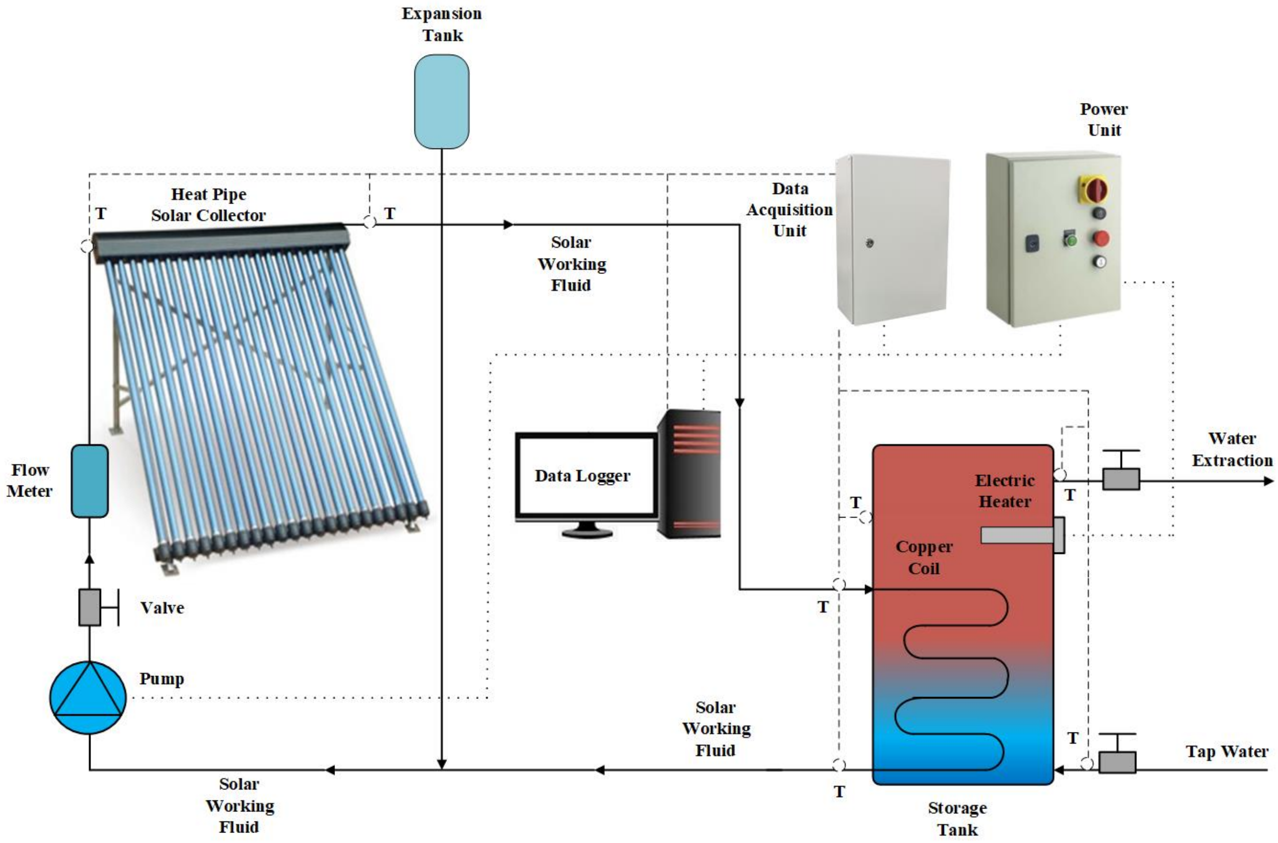


Fig. 1. Schematic of a HPSWH system (Shafieian et al., 2019d).

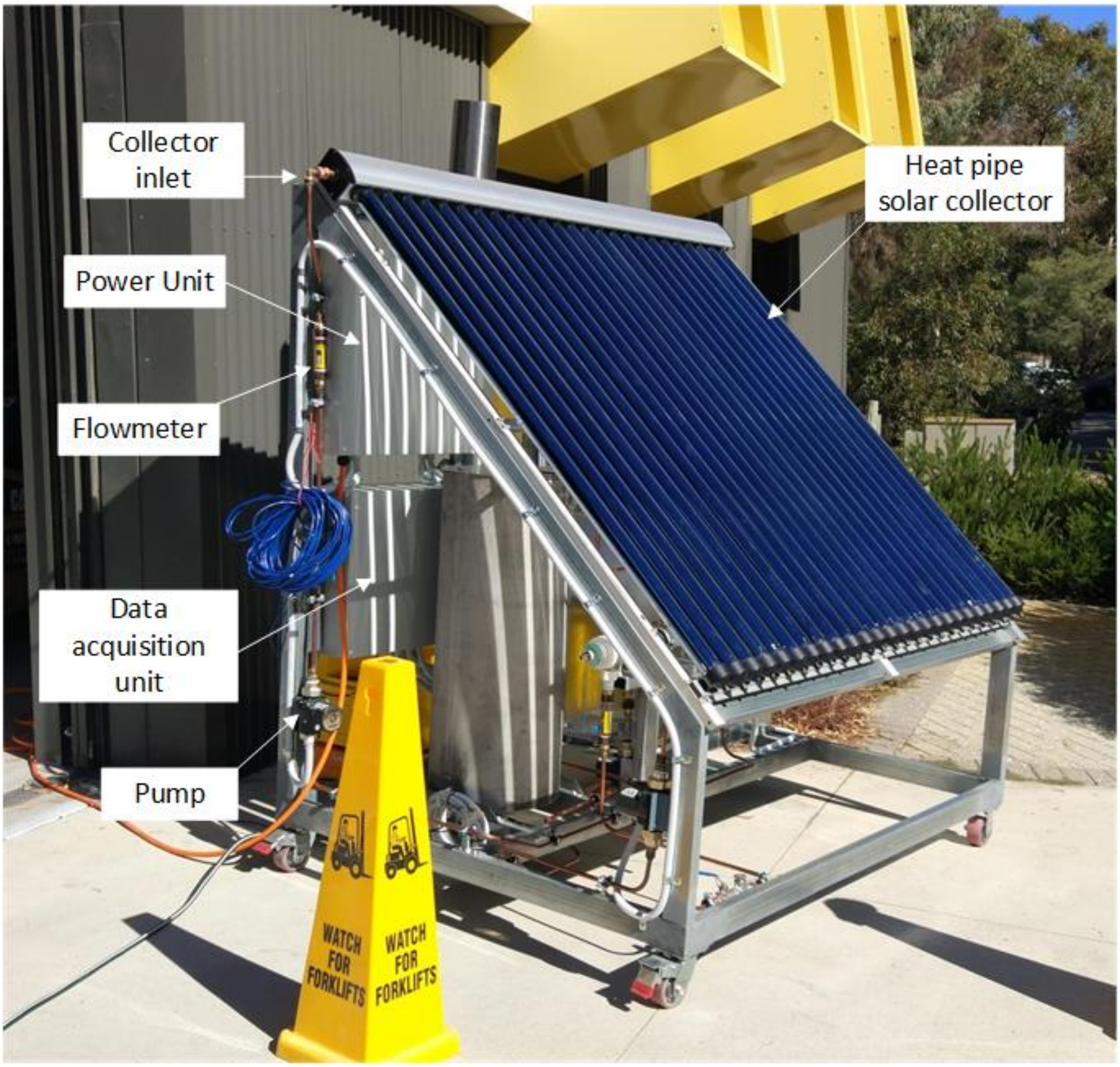


Fig. 2. The experimental rig

2.2. Annual climatic conditions data

The climatic data (e.g., solar radiation and ambient temperature) was continuously recorded in one minute intervals by a weather station located in Joondalup Campus of Edith Cowan University. The climatic data of a year was collected, divided based on four seasons, and used for further analysis. In Perth region, spring and summer approximately comprise the months of September to November and December to February. March to May and June to August are respectively autumn and winter in this geographical area.

2.3. Experimental data collection

The central control unit used in the system consisted of a National Instrument Data Acquisition (NI-DAQ) system, a control unit, and a computer. Seven Type T- Class1 thermocouples (TC Ltd.) were installed at various locations of the system. The locations of the thermocouples are shown in Fig. 1. These thermocouples were monitored using NI-DAQ system. These sets of data were recorded at 10-second intervals using LabVIEW 2014 software. The experimental data, including the inlet and outlet temperatures of the collector, and the solar working fluid mass flow rate, along with the collected climatic data were used to train, validate, and test different modelling methods as well as proposing equations which best describe the performance of the system.

3. Modelling approaches

3.1. Artificial neural network (ANN) method

Inspired by biological neural networks, ANN is an adaptive identification approach that can be used for identifying artificial models for complex systems by implementing an iterative algorithm to construct the network. Basically, ANN applies two processing tools. The first tool is the perception which is a neuron nonlinear model. Perception is composed of a linear combiner and a nonlinear activation element. The second tool is the basic function neuron which implements a nonlinear function on the input vector. The usual structure of ANN is a multi-layer perceptron (MLP) which is a feed-forward network. There are one input layer, multiple hidden layers, and one output layer in a preceptor (as shown in Figure 3 which is the structure of the artificial neural network used in this study). The neural network toolbox of MATLAB is utilized in this study for identifying a model for the HSPC. Three climatic and operational parameters (i.e. inlet temperature of the HPSC, ambient temperature, and solar radiation) were considered as inputs. Outlet temperature, which is the main contributing

parameter in the thermal efficiency of solar collectors, is considered as the output parameter. The input-output data is divided into training (80% of data) and validation (20% of data) and the number of hidden layers in the input was 10.

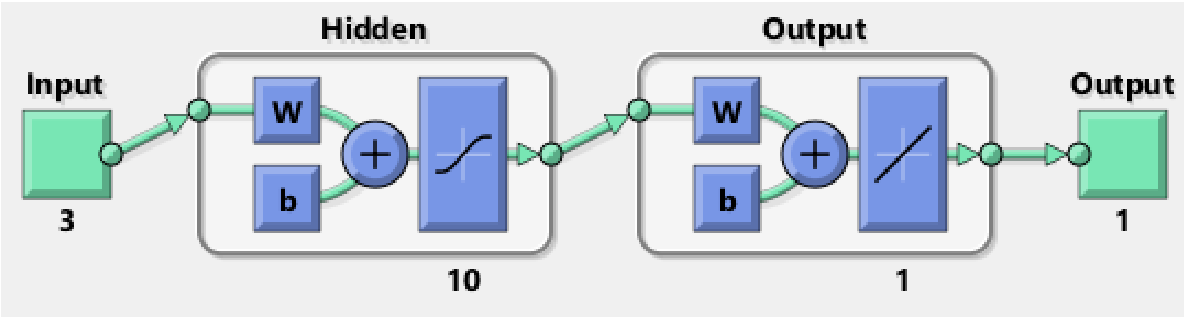


Fig. 3. The ANN structure

A sample of ANN performance is shown in Fig. 4 which presents the mean square error in each epoch for the training, validation, and performance test. The errors have reduced after each epoch. The best validation performance corresponding to the lowest validation error was attained at epoch 11.

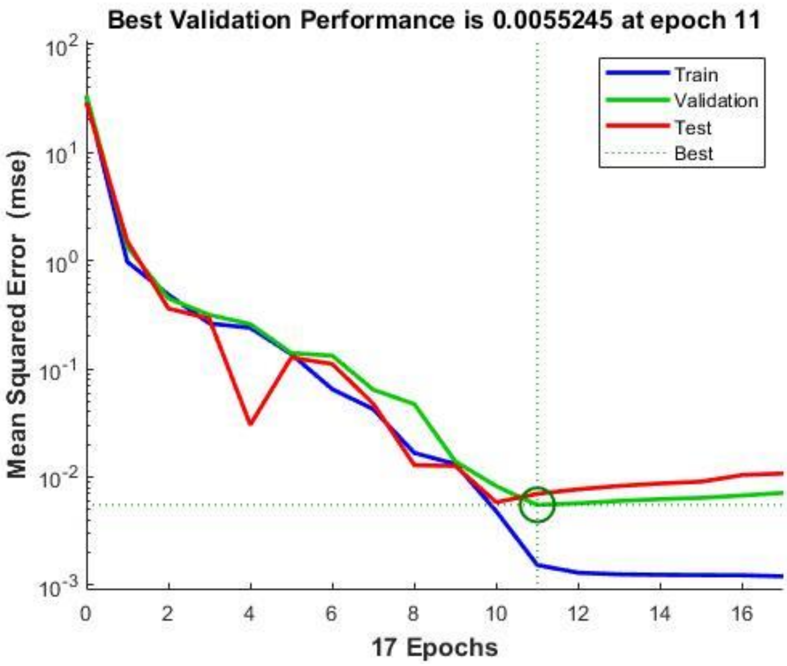


Fig. 4. ANN performance

A sample of the ANN regression plots are illustrated in Fig. 5 which shows the difference between estimated output and the target. In a perfect training, the estimated outputs and targets would be equal; however, there is a small error in practice. The top left graph indicates the network output versus target for training while the top right graph shows the same parameter for validation. Bottom graphs represent the network output versus target for test and all data. The dashed line in all plots indicates the perfect fit between the estimated outputs and the targets while the solid lines indicate the best fit linear regression. The value of R for all graphs is close to 1 showing that there is a very exact linear correlation between outputs and targets. Further studies regarding the precision of the developed ANN model can be found in Appendix.

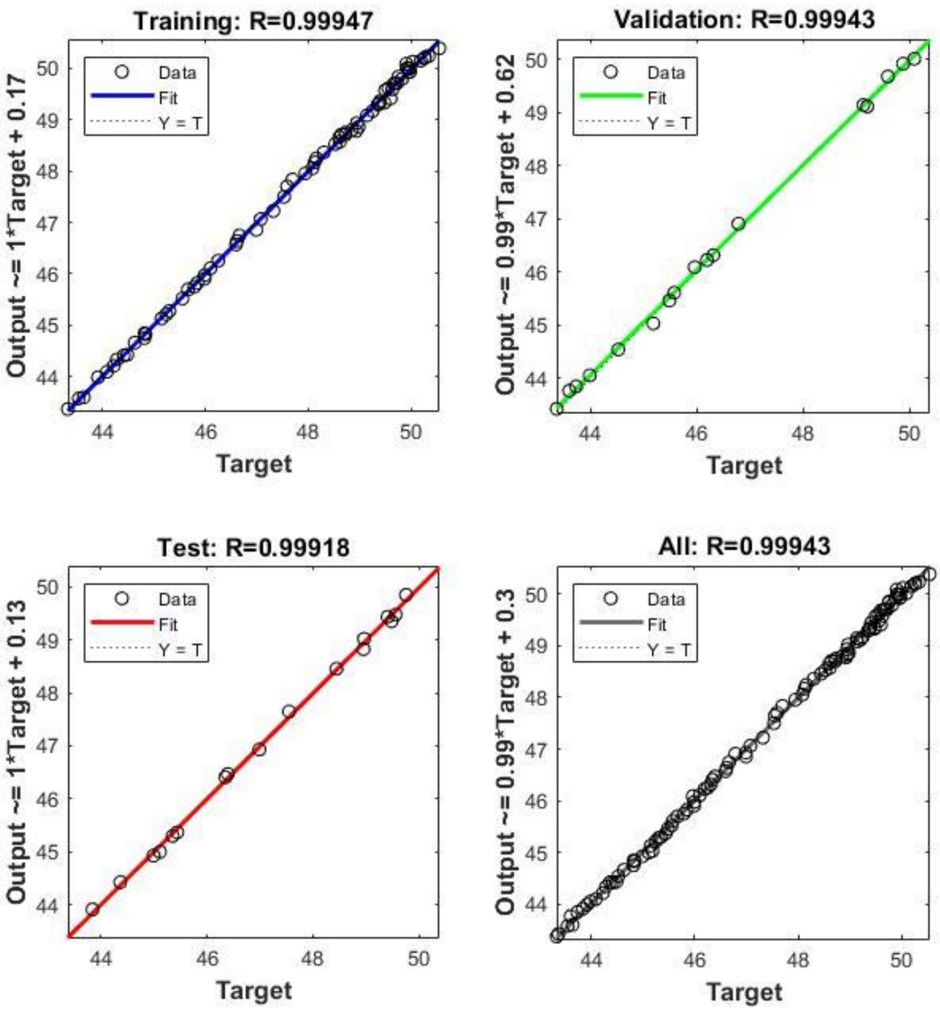


Fig. 5. Network output versus target for training, validation, test, and all data

3.2. Adaptive Neuro Fuzzy Inference System (ANFIS) method

ANFIS is an artificial neural network and relies on Takagi-Sugeno fuzzy inference system. This method is benefited from the advantage of both fuzzy and neural networks. The inference in ANFIS is based on a set of fuzzy rules for finding the nonlinear functions with learning ability. There are five layers in ANFIS. In the first layer, called the fuzzification layer, the input data is given and the membership functions and degrees can be assigned. The second layer, called the rule layer, generates the firing strengths of rules. The calculated strengths are then normalized in the third layer. In the fourth layer, the normalized input is given and the

consequent parameters can be computed. Finally, the output of the fourth layer, the defuzzification values, are sent to the last layer to generate the output.

MATLAB was used in this study to identify the neuro-fuzzy model of HPSCs. The array of input data was created in MATLAB workspace and then was loaded to neuro-fuzzy designer. The ANFIS structure for identifying the HPSC model is shown in Figure 6. Five Gaussian membership functions were selected for each input. The type of output transfer function was constant and the FIS structure was created by a grid partition of the inputs.

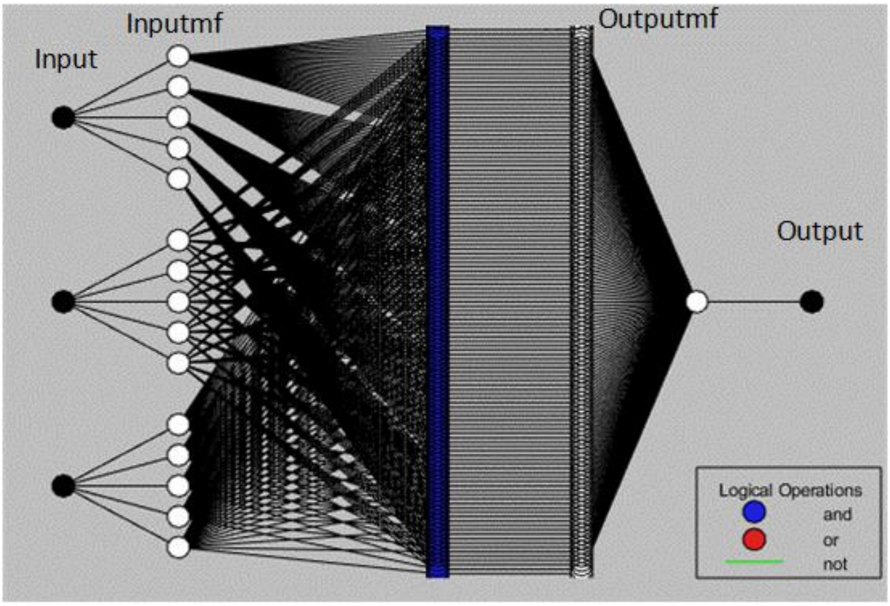


Fig. 6. The ANFIS structure for identifying HPSC model

The training algorithm in MATLAB is based on a mixed least square and back propagation gradient descent methods. The backpropagation is applied to the parameters of input transfer function while the least square method is used for parameters of output membership functions. This optimization approach in MATLAB is called hybrid. The ANFIS editor can tune an initial fuzzy inference system and validate data to prevent data overfitting. Validation data was used to check the performance of the identified model. These data are completely different than the

training data and are a good representative of HPSC performance. Also checking data can be used to prevent overfitting of the training data set.

3.3. Fuzzy method

Fuzzy modelling was also used to attain a model for HPSCs in solar water heating systems. The input variables of the fuzzy system are mapped via a set of membership functions (i.e. fuzzy sets). The conversion of inputs to a fuzzy value is named fuzzification. After fuzzification, the fuzzy operators (AND or OR) will be applied and the implications of the rules will be generated. Then the aggregation of the consequences across all rules will be computed. Finally, through defuzzification, the outputs will be generated. In this study, a set of seven triangular-shaped membership functions were used for fuzzification. Although several other membership functions were tried, the results led to diverging errors.

3.4. Thermal Resistance Network (TRN) method

The TRN method has been frequently applied in the literature to theoretically model the thermal performance of HPSCs. The reason for this popularity is the complexity of the direct simulation of the continuous phase change processes of the working fluid happening inside the heat pipes of a HPSC (Shafieian et al., 2019b). The mathematical equations to simulate the thermal processes inside the components of a heat pipe solar collector including absorber, heat pipe, and manifold, along with the comprehensive computation process and flowchart can be found in authors' previous study (Shafieian et al., 2019b).

As shown in Fig. 7, the overall thermal resistance between the surrounding area and absorber surface ($R_{t,c}$ in equation 1) is the summation of: (a) summation of radiative and natural convective thermal resistances existing between inner glass and absorber surface ($R_{ab\text{-}gi}$); (b) inner glass conductive thermal resistance (R_{gi}); (c) radiative thermal resistance existing between inner and outer layers of glass ($R_{gi\text{-}go}$); (d) conductive thermal resistance of outer glass

(R_{go}); and (e) combination of forced convective and radiative thermal resistances between the outer glass and surrounding area ($R_{go\text{-}amb}$).

$$R_{t,c} = R_{ab,gi} + R_{gi} + R_{gi-go} + R_{go} + R_{go-amb} \tag{1}$$

Taking Fig. 7 into account, the total evaporator-condenser thermal resistance of a heat pipe ($R_{t,hp}$ in equation 2) is the summation of: (a) convective thermal resistance of evaporator (R_h); (b) convective thermal resistance of condenser (R_c); (c) thermal resistances of residuals forming on the evaporator and condenser outer walls ($R_{f,h}$ and $R_{f,c}$, respectively); (d) evaporator and condenser conductive thermal resistances ($R_{w,h}$ and $R_{w,c}$, respectively); (e) conductive thermal resistance of wick structure ($R_{wi,e}$); (f) evaporator and condenser thermal resistances ($R_{i,e}$ and $R_{i,c}$, respectively).

$$R_{t,hp} = R_h + R_{f,h} + R_{w,h} + R_{wi,e} + R_{i,e} + R_v + R_{i,c} + R_{w,c} + R_{f,c} + R_c \tag{15}$$

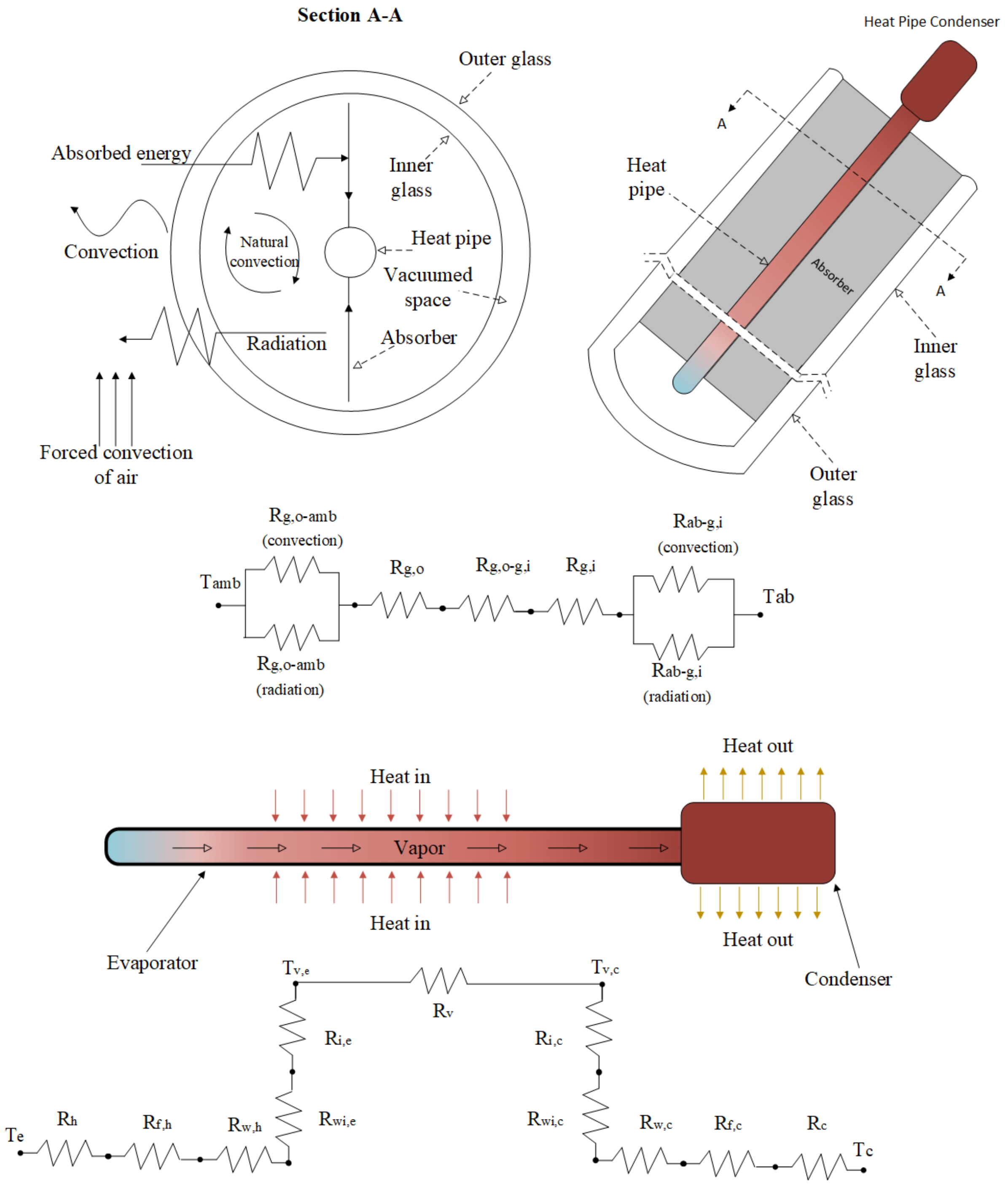


Fig. 7. Heat transfer processes inside HPSCs (Shafieian et al., 2019c)

3.5. Prediction evaluation parameters

Different accuracy evaluation criteria including Root Mean Square Error (*RMSE*), Mean Absolute Percentage Error (*MAPE*), Variance Accounted For (*VAF*), and R-squared (R^2) were considered in this study to evaluate the prediction accuracy of various proposed methods. As a quadratic scoring rule, RMSE evaluates the average value of the errors and can be calculated by (Kalani et al., 2017):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{3}$$

where x_i is the measured value while $\hat{x}_i$ represents the estimated value by the model. In addition, the number of samples is shown with n in this equation.

MAPE and *VAF* are obtained from (Kalani et al., 2017):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \tag{4}$$

$$VAF = \left[1 - \frac{var(x - \hat{x})}{var\ (x)}\right] \tag{5}$$

The parameter R^2 which is a measure of the reliability of the model can be determined by (Al-Waeli et al., 2019):

$$R^2 = \frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{6}$$

where $\bar{x}$ represents the mean value of the experimental data.

3.6. Performative parameters

One of the most important parameters for performance evaluation of any solar collector is its thermal efficiency. The thermal efficiency of the HPSC can be calculated by (Azad, 2008):

$$\eta_c = \frac{m_w C_w (T_{w,o-} T_{w,i})}{G A_c} \quad (19)$$

where m_w (kg/s) and C_w (J/kgK) respectively represent solar working fluid mass flow rate and specific heat capacity. $T_{w,i}$ (°C) and $T_{w,o}$ (°C) in this equation are the collector inlet and outlet temperatures, respectively.

Another important parameter for assessing a solar collector is exergy efficiency, which specifies the time and magnitude of high energy losses. Exergy efficiency can be widely used to provide opportunities for thermodynamic enhancement and can be calculated by (Gunerhan and Hepbasli, 2007):

$$\eta_{sc} = \frac{Ex_u}{Ex_{sc}} \quad (23)$$

where Ex_u (kW) is the useful exergy delivered by the HPSC while Ex_{sc} (kW) is the absorbed exergy by the solar collector. More information regarding the thermal and exergy efficiencies along with equations to determine the mentioned parameters can be found in (Gunerhan and Hepbasli, 2007; Shafieian et al., 2019c).

4. Results and discussions

Table 1 compares the performance of various mathematical conventional and data-based methods to predict the performance of HPSCs based on several evaluation parameters in four seasons. These parameters include the parameters which were explained in Section 3.5 as well as Absolute Residual Error (*ARE*). Closer values of *VAF* and R^2 parameters to 1 as well as lower values of *RMSE*, *ARE* and *MAPE* parameters (i.e. closer values to zero) refer to lower variation between the experimental and predicted values.

The results reveal that two of the data-based methods (i.e. ANN and ANFIS) are more accurate in simulation of HPSCs compared to TRN method. In all seasons and based on all evaluation

parameters, the predicted results by ANN and ANFIS methods show less variations with the experimental data. For instance, *VAF* and R^2 parameters in Autumn are respectively 0.99489 and 0.989 for ANN method, while these parameters are respectively 0.99188 and 0.95493 for ANFIS method and 1.00015 and 0.85703 for TRN method. These values as well as others presented in the table clearly prove the advantages of ANN and ANFIS methods over TRN method.

It is worth noting that modelling HPSCs using the Fuzzy method resulted in either large errors or divergence of the program. Hence, Fuzzy method is recognized as the worst method among the studied methods and is not recommended for modelling HPSCs.

Considering the first four evaluation parameters (i.e. *RMSE*, *VAF*, *ARE* and *MAPE*), no significant difference can be seen between the accuracy of ANN and ANFIS methods. ANN performs better based on some parameters and in some seasons, while ANFIS is more accurate in others; nevertheless, the difference is negligible. However, by taking the important parameter of R^2 into account, one can conclude that the best method for predicting the performance of HPSCs is ANN. This method is followed by the ANFIS and TRN methods while Fuzzy method is not recommended for this purpose.

Table 1. Accuracy comparison of various methods in predicting the performance of HPSCs

Season	**Method**	**RMSE**	**VAF**	**MAPE**	**ARE**	**R^2**
Spring	ANN	0.00720	0.98826	0.00119	0.05244	0.98079
	ANFIS	0.00335	0.99729	0.00012	0.0061	0.86222
	TRN	0.24826	0.99632	0.01389	0.7824	0.8674
Summer	ANN	0.00525	0.99942	0.00126	0.0713	0.98974
	ANFIS	0.00461	1.00003	0.00037	0.0173	0.94201

	TRN	0.21473	1.02035	0.01315	0.1742	0.89965
	ANN	0.01348	0.99489	0.00335	0.15722	0.98903
Autumn	ANFIS	0.02553	0.99188	0.00228	0.06422	0.95493
	TRN	0.33123	1.00015	0.02864	1.003	0.85703
	ANN	0.00531	0.99941	0.00149	0.05385	0.99209
Winter	ANFIS	0.02376	0.99881	0.00233	0.0897	0.95547
	TRN	0.32865	0.99746	0.02618	0.2368	0.87684

Obtaining an equation which relates the outlet temperature of the HPSC to the climatic and operational parameters is crucial for two main reasons. First, it can be used as an effective tool in the optimum design of heat pipe solar systems before the manufacturing process. Secondly, it can be used in the development of new solar systems where limited resources of experimental or theoretical data are available.

The parameter which is used commonly for obtaining such equations is:

$$x = \frac{T_{c,i} - T_{amb}}{G} \tag{7}$$

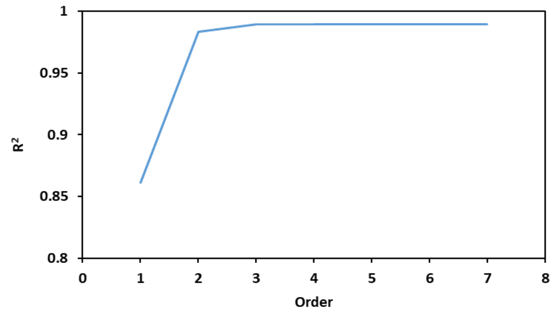
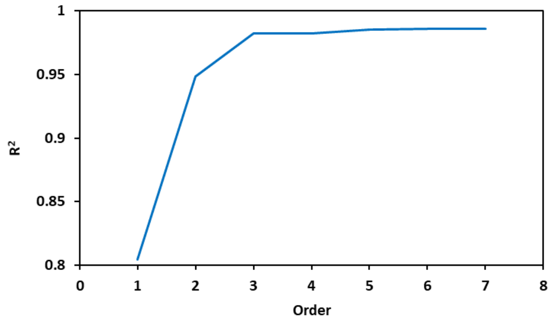
where $T_{c,i}$ (°C) and T_{amb} (°C) are the collector inlet and ambient temperatures. G (W/m^2) in this equation represents the solar radiation. The equation for determining the outlet temperature of the HPSC can be written as:

$$T_{c,o} = a_1 x^n + a_2 x^{n-1} + a_3 x^{n-3} + \cdots + a_{n+1} \qquad n = 1,2,\ldots,i \tag{8}$$

where *i* represents the order of the equation. It is worth noting that the superscripts in this equation (i.e. *n*, *n-1*, *n-2, …*) should be equal or bigger than zero and cannot be negative.

Table 2 shows the values of constants in Eq. (8) for various orders along with the equations' accuracies. The optimum equation is the one with high accuracy and at the same time with low computation cost (i.e. order number). The optimum equations to relate the outlet temperature of the HPSC to the climatic and operational parameters in summer is of the order of two. An equation with the order of three best describes the performance of the HPSC in spring, autumn, and winter. The main reason for this behaviour may be related to this fact that the number of sudden fluctuations in climatic conditions is high during these three seasons. At the same time, these fluctuations are quite unpredictable and happen rapidly, making the response time of the system rather high. As a result, an equation with higher order is required to predict the performance of the HPSC in these seasons compared to summer. The climatic conditions are more stable in summer and trends are relatively predictable. Overall, Table 3 summarizes the obtained optimum equations to describe the performance of HPSCs for four seasons.

Table 2. Constants of Eq. (8) for various orders along with the equations' accuracies

Season	Order	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	Accuracy (R^2)
Spring	1	575.25	25.45							
	2	-1771	1533	14.617						
	3	520637	-70611	3082.7	1.78					
	4	-2e7	4e6	-240953	6350	-18.97				
	5	-1.6e11	1.58e10	-6.08e8	1.16e7	-1.07e5	425.8			
	6	1.99e14	-2.4e13	1.18e12	-3.1e10	4.59e8	-3.59e6	1.16e4		
	7	-1.2e16	1.85e15	4.40e12	4.4e12	-9.44e10	1.20e9	-8.40e6	2.49e4	
Summer	1	709.36	33.236							
	2	-6601.1	1011.4	29.921						
	3	4e6	-250392	6515.1	-10.382					
	4	8.26e7	-1.13e7	5.40e5	-1.01e4	101.6				
	5	-6.31e9	1.16e9	-8.35e7	2.91e6	-4.83e4	342.4			
	6	-2.5e11	4.55e10	-3.21e9	1.10e8	-1.81e6	1.23e4	23.62		
	7	1.04e14	-2.5e13	2.58e12	-1.4e11	4.75e9	-9.22e7	9.76e5	-4317	
Autumn	1	328.93	34.476							
	2	-1.07e3	1231	17.92						
	3	327586	-53409	2951	-3.295					
	4	-912213	488519	-63520	3217.5	-5.7754				
	5	-1.28e9	4.48e8	-6.15e7	4.10e6	-1.33e5	1722			
	6	7.37e10	-3.3e10	5.99e9	-5.73e8	3.02e7	-8.3e5	9359		
	7	2.1e12	-9.9e11	1.94e11	-2.1e10	1.24e9	-4.38e7	8.17e5	-6143	

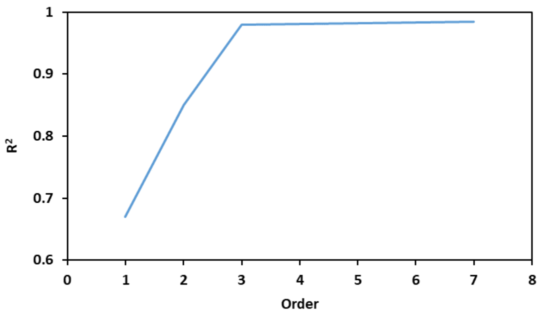
	1	62.73	42.1							
	2	1560.6	-183.1	50.885						
	3	87188	-20195	1539.2	7.8148					
Winter	4	-4e6	2e6	-197316	10712	-163.71				
	5	-1.2e11	8.49e9	-1.96e8	1.05e6	1.79e4	-145.4			
	6	1.64e14	-1.8e13	8.22e11	-1.9e10	2.55e8	-1.74e6	4823		
	7	-3.7e16	4.86e15	-2.7e14	8.36e12	-1.52e11	1.63e9	-9.59e6	2.38e4	

Table 3. Optimum equations to describe the performance of HPSCs

Season	Equation
Spring	$T_{c,o} = 520637x^3 - 70611x^2 + 3082.7x + 1.78$
Summer	$T_{c,o} = -6601.1x^2 + 1011.4x + 29.921$
Autumn	$T_{c,o} = 327586x^3 - 53409x^2 + 2951x - 3.295$
Winter	$T_{c,o} = 87188x^3 - 20195x^2 + 1539.2x + 7.8148$

Based on the results which were discussed in previous sections, ANN was recognised as the best method for theoretical analysis of HPSCs. Therefore, its performance in predicting the thermal efficiency of the solar collector is studied and the results are shown in Fig. 8. It is worth mentioning that the results presented in this figure are seasonal averaged values. The highest difference between the experimental and theoretical thermal efficiencies is observed in autumn and winter with 3.56% and 3.55%, respectively. This is followed by spring and summer with respectively 2.64% and 2.79% differences. Overall, these values again prove the accuracy of the ANN method for predicting the performative parameters of HPSCs in solar systems. As expected, due to high solar radiation in summer, the highest thermal efficiency occurs in this season with around 64%. This is followed by spring and autumn with respectively 60.4% and 53.3%. Winter with thermal efficiency of 47.8% has the lowest thermal efficiency in all seasons.

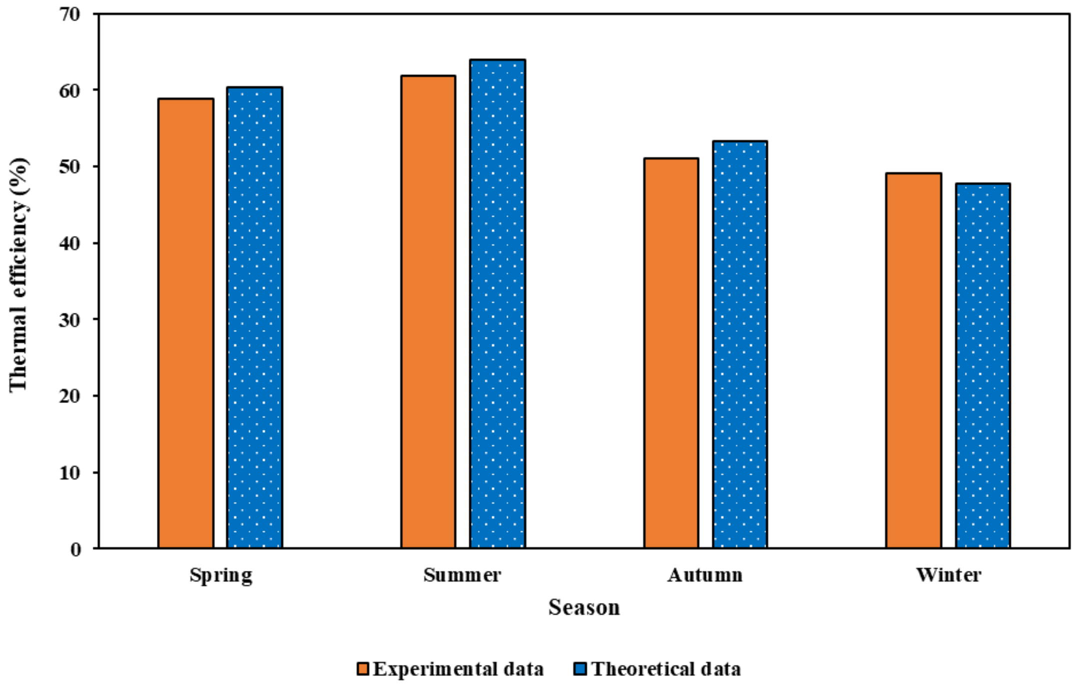


Fig. 8. Experimental and predicted thermal efficiencies of the HPSC in different seasons

The accuracy of the ANN method in forecasting the exergy efficiency, which is another important parameter in studying HPSCs, is investigated and the results are presented in Fig. 9. It is worth mentioning that the results presented in this figure are seasonal averaged values. The divergences between the experimental and predicted data almost followed the same trend as those obtained for thermal efficiencies. The highest difference is observed to occur in autumn and winter with 1.52% and 1.5%, respectively. The divergence in spring is observed to be 1.2% while this parameter is around 1% in summer. These low divergence values indicate the capability of ANN method to be used effectively in theoretical modelling of HPSCs in solar systems. The HPSC shows its best performance in hot seasons by having the exergy efficiencies of 6.83% and 6.03% in summer and spring, respectively. The exergy efficiencies in winter and autumn are respectively 5.38% and 5.81%.

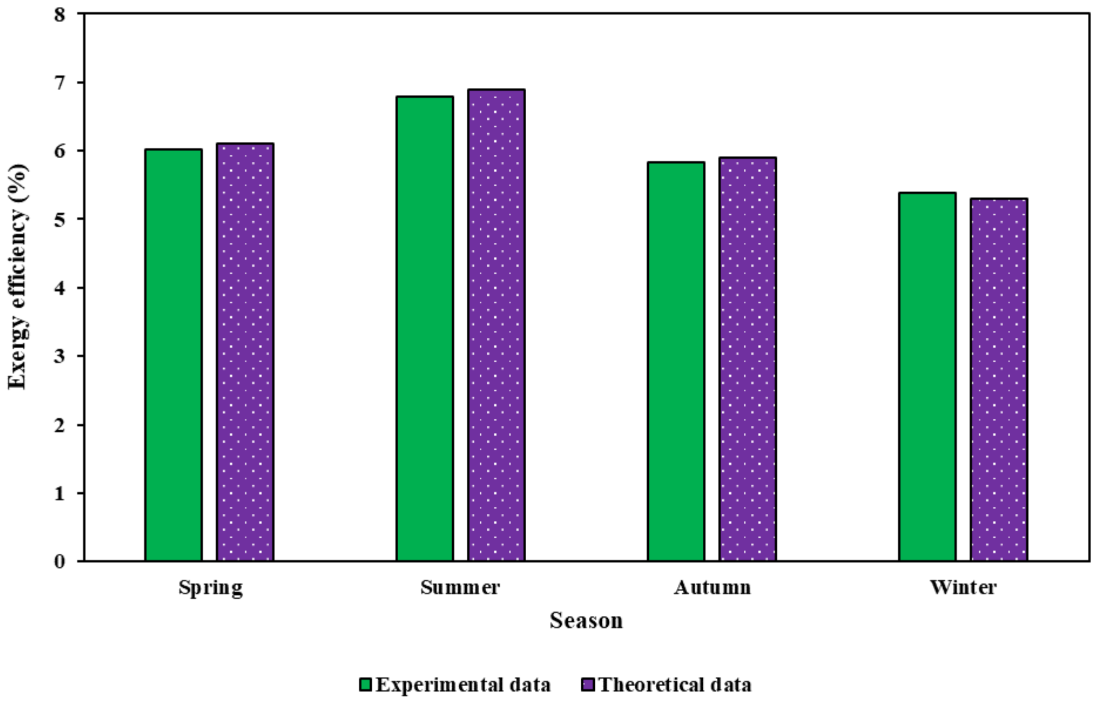


Fig. 8. Experimental and theoretical exergy efficiencies of the HPSC in different seasons

For further accuracy evaluation of the developed ANN method, the experimental data presented by Daghigh and Zandi (Daghigh and Zandi, 2019) was used and the predicted data by the ANN method were compared with them. Figure 9 compares the experimental and theoretical outlet temperatures of the HPSC. The climatic and operational conditions under which these data were obtained can be found in (Daghigh and Zandi, 2019). The predicted data are in good agreement with the experimental ones by having the highest difference of 2.57% which happens at the beginning of the operation. This may be attributed to the fact that at the beginning of the operation, the system is not stable and at the same time the climatic conditions fluctuate more in the morning compared to the other times of the day.

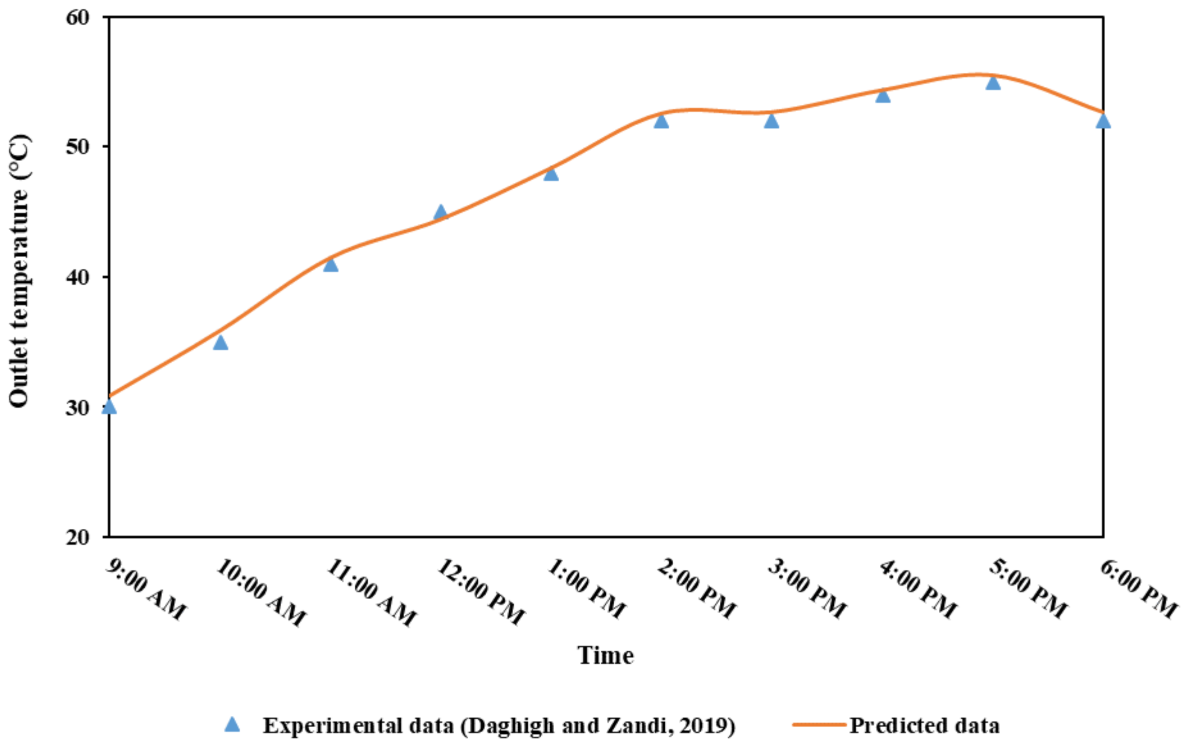


Fig. 9. Comparison between theoretical and experimental outlet temperatures of the HPSC

5. Conclusions

Various data-based and conventional models, including Artificial Neural Network (ANN), Thermal Resistance Network (TRN), Artificial Neuro Fuzzy Inference System (ANFIS), and Fuzzy methods, were developed in this study to simulate the performance of HPSCs. The predicted results were compared with the annual experimental data which were obtained by conducting many sets of experiments under real climatic conditions of Western Australia. The results of various accuracy criteria, including Root Mean Square Error (*RMSE*), Mean Absolute Percentage Error (*MAPE*), Variance Accounted For (*VAF*), and R-squared (R^2), proved that the best method to predict the performance of HPSCs was ANN. The results also showed that ANN method was followed by ANFIS and TRN methods in terms of accuracy while Fuzzy method had the worst performance in simulation of HPSCs' processes. Moreover, the optimum equations to describe the performance of HPSCs for four seasons was obtained and verified.

Appendix

The training state of ANN in Figure A1 shows the gradient, mu, and validation checks. The gradient is the amount of backpropagation gradient on each epoch in logarithmic scale. The ANN has reached to the local minimum (0.0018) at epoch 26. Validation fails is correspondent to the iterations when MSE of validation is increased. The successive increase in MSE means the network is over-trained. MALTLAB stops training after 6 successive fails. Here, it has stopped at epoch 26.

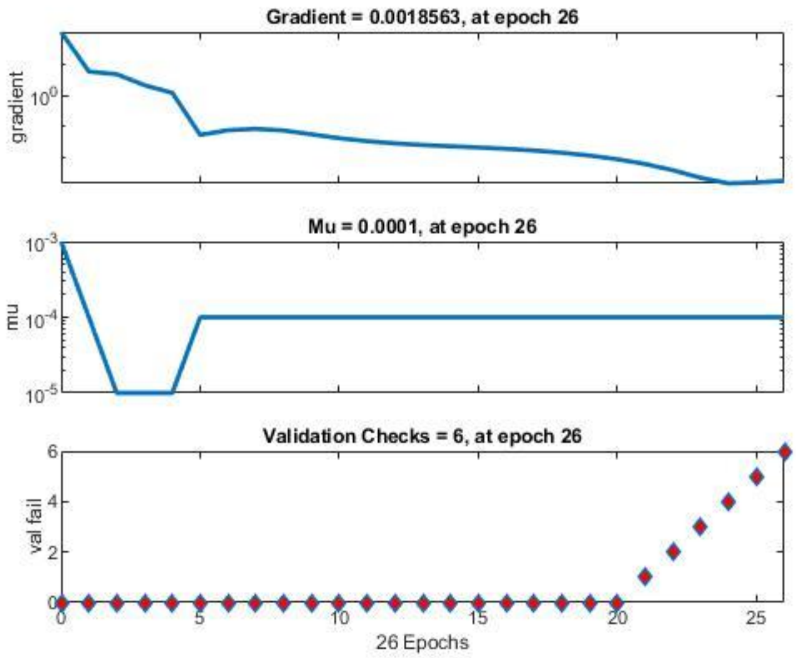


Fig. A1. The ANN training state

The ANN error histogram representing the errors between target and predicted values is shown in Figure A2. The 20 vertical bars or bins are illustrated on the graph which divide the total error of ANN into 20 sections. Each bin indicates the number of data samples from the dataset within the range. This graph determines the accuracy of fitting between the model and available data.

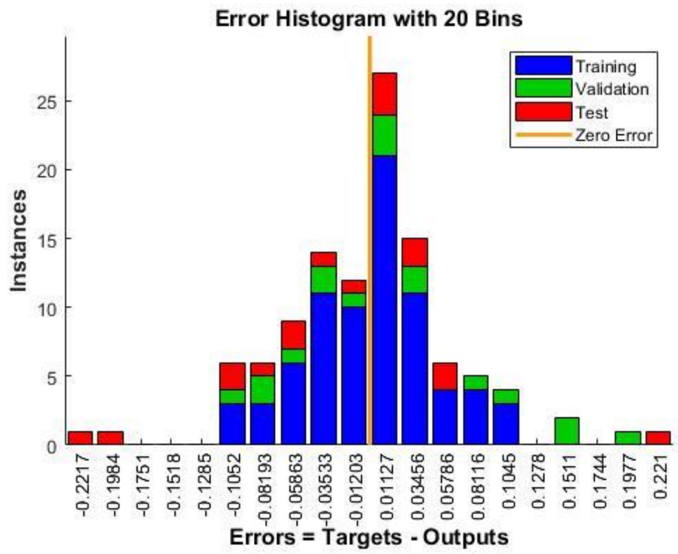


Fig. A2. The ANN error histogram

References:

Al-Waeli, A.H., Sopian, K., Yousif, J.H., Kazem, H.A., Boland, J., Chaichan, M.T., 2019. Artificial neural network modeling and analysis of photovoltaic/thermal system based on the experimental study. Energy Conversion and Management 186, 368-379.

Azad, E., 2008. Theoretical and experimental investigation of heat pipe solar collector. Experimental Thermal and Fluid Science 32(8), 1666-1672.

Bui, D.-K., Nguyen, T.N., Ngo, T.D., Nguyen-Xuan, H., 2020. An artificial neural network (ANN) expert system enhanced with the electromagnetism-based firefly algorithm (EFA) for predicting the energy consumption in buildings. Energy 190, 116370.

Caner, M., Gedik, E., Keçebaş, A., 2011. Investigation on thermal performance calculation of two type solar air collectors using artificial neural network. Expert Systems with Applications 38(3), 1668-1674.

Carmona, M., Palacio, M., 2019. Thermal modelling of a flat plate solar collector with latent heat storage validated with experimental data in outdoor conditions. Solar Energy 177, 620-633.

Chow, T.-T., Dong, Z., Chan, L.-S., Fong, K.-F., Bai, Y., 2011. Performance evaluation of evacuated tube solar domestic hot water systems in Hong Kong. Energy and Buildings 43(12), 3467-3474.

Daghigh, R., Shafieian, A., 2016. Theoretical and experimental analysis of thermal performance of a solar water heating system with evacuated tube heat pipe collector. Applied Thermal Engineering 103, 1219-1227.

Daghigh, R., Zandi, P., 2019. Improving the performance of heat pipe embedded evacuated tube collector with nanofluids and auxiliary gas system. Renewable energy 134, 888-901.
Diallo, T.M., Yu, M., Zhou, J., Zhao, X., Shittu, S., Li, G., Ji, J., Hardy, D., 2019. Energy performance analysis of a novel solar PVT loop heat pipe employing a microchannel heat pipe evaporator and a PCM triple heat exchanger. Energy 167, 866-888.
Diez, F., Navas-Gracia, L., Martínez-Rodríguez, A., Correa-Guimaraes, A., Chico-Santamarta, L., 2019. Modelling of a flat-plate solar collector using artificial neural networks for different working fluid (water) flow rates. Solar Energy 188, 1320-1331.
El-Sebaii, A., Shalaby, S., 2012. Solar drying of agricultural products: A review. Renewable and Sustainable Energy Reviews 16(1), 37-43.
Elsheniti, M.B., Kotb, A., Elsamni, O., 2019. Thermal performance of a heat-pipe evacuated-tube solar collector at high inlet temperatures. Applied Thermal Engineering 154, 315-325.
Ersöz, M.A., 2016. Effects of different working fluid use on the energy and exergy performance for evacuated tube solar collector with thermosyphon heat pipe. Renewable energy 96, 244-256.
Esen, H., Esen, M., Ozsolak, O., 2017. Modelling and experimental performance analysis of solar-assisted ground source heat pump system. Journal of Experimental & Theoretical Artificial Intelligence 29(1), 1-17.
Esen, H., Inalli, M., Sengur, A., Esen, M., 2008a. Artificial neural networks and adaptive neuro-fuzzy assessments for ground-coupled heat pump system. Energy and Buildings 40(6), 1074-1083.
Esen, H., Inalli, M., Sengur, A., Esen, M., 2008b. Forecasting of a ground-coupled heat pump performance using neural networks with statistical data weighting pre-processing. International Journal of Thermal Sciences 47(4), 431-441.
Esen, H., Inalli, M., Sengur, A., Esen, M., 2008c. Modelling a ground-coupled heat pump system using adaptive neuro-fuzzy inference systems. International Journal of Refrigeration 31(1), 65-74.
Esen, H., Inalli, M., Sengur, A., Esen, M., 2008d. Performance prediction of a ground-coupled heat pump system using artificial neural networks. Expert Systems with Applications 35(4), 1940-1948.
Esen, H., Inalli, M., Sengur, A., Esen, M., 2008e. Predicting performance of a ground-source heat pump system using fuzzy weighted pre-processing-based ANFIS. Building and Environment 43(12), 2178-2187.
Esen, H., Ozgen, F., Esen, M., Sengur, A., 2009. Artificial neural network and wavelet neural network approaches for modelling of a solar air heater. Expert systems with applications 36(8), 11240-11248.
Esen, M., 2004. Thermal performance of a solar cooker integrated vacuum-tube collector with heat pipes containing different refrigerants. Solar Energy 76(6), 751-757.
Esen, M., Esen, H., 2005. Experimental investigation of a two-phase closed thermosyphon solar water heater. Solar Energy 79(5), 459-468.
Farajzadeh, E., Movahed, S., Hosseini, R., 2018. Experimental and numerical investigations on the effect of Al2O3/TiO2H2O nanofluids on thermal efficiency of the flat plate solar collector. Renewable energy 118, 122-130.
Fischer, S., Frey, P., Drück, H., 2012. A comparison between state-of-the-art and neural network modelling of solar collectors. Solar energy 86(11), 3268-3277.
Gunerhan, H., Hepbasli, A., 2007. Exergetic modeling and performance evaluation of solar water heating systems for building applications. Energy and Buildings 39(5), 509-516.
Kalani, H., Sardarabadi, M., Passandideh-Fard, M., 2017. Using artificial neural network models and particle swarm optimization for manner prediction of a photovoltaic thermal nanofluid based collector. Applied Thermal Engineering 113, 1170-1177.

Kalogirou, S.A., 2004. Solar thermal collectors and applications. Progress in energy and combustion science 30(3), 231-295.
Kumar, R., Rosen, M.A., 2011. A critical review of photovoltaic–thermal solar collectors for air heating. Applied Energy 88(11), 3603-3614.
Liu, Z., Li, H., Liu, K., Yu, H., Cheng, K., 2017. Design of high-performance water-in-glass evacuated tube solar water heaters by a high-throughput screening based on machine learning: A combined modeling and experimental study. Solar Energy 142, 61-67.
Liu, Z., Li, H., Zhang, X., Jin, G., Cheng, K., 2015. Novel method for measuring the heat collection rate and heat loss coefficient of water-in-glass evacuated tube solar water heaters based on artificial neural networks and support vector machine. Energies 8(8), 8814-8834.
Marugán, A.P., Márquez, F.P.G., Perez, J.M.P., Ruiz-Hernández, D., 2018. A survey of artificial neural network in wind energy systems. Applied energy 228, 1822-1836.
Mohandas, P., Dhanaraj, J.S.A., Gao, X.-Z., 2019. Artificial Neural Network based Smart and Energy Efficient Street Lighting System: A Case Study for Residential area in Hosur. Sustainable Cities and Society 48, 101499.
Mohanty, S.P., Rout, A., Patra, P.K., Sahoo, S.S., 2017. Soft computing techniques for a solar collector using solar radiation data. Energy Procedia 109, 439-446.
Naik, B.K., Varshney, A., Muthukumar, P., Somayaji, C., 2016. Modelling and performance analysis of U type evacuated tube solar collector using different working fluids. Energy Procedia 90, 227-237.
Sabiha, M., Saidur, R., Hassani, S., Said, Z., Mekhilef, S., 2015a. Energy performance of an evacuated tube solar collector using single walled carbon nanotubes nanofluids. Energy Conversion and Management 105, 1377-1388.
Sabiha, M., Saidur, R., Mekhilef, S., Mahian, O., 2015b. Progress and latest developments of evacuated tube solar collectors. Renewable and Sustainable Energy Reviews 51, 1038-1054.
Saikia, S.S., Nath, S., Bhanja, D., 2019. Effect of vacuum deterioration on thermal performance of coaxial evacuated tube solar collector considering single and two phase flow modelling: A numerical study. Solar Energy 177, 127-143.
Shafieian, A., Khiadani, M., 2019. A novel solar-driven direct contact membrane-based water desalination system. Energy Conversion and Management 199, 112055.
Shafieian, A., Khiadani, M., Nosrati, A., 2018. A review of latest developments, progress, and applications of heat pipe solar collectors. Renewable and Sustainable Energy Reviews 95, 273-304.
Shafieian, A., Khiadani, M., Nosrati, A., 2019a. Strategies to improve the thermal performance of heat pipe solar collectors in solar systems: A review. Energy conversion and management 183, 307-331.
Shafieian, A., Khiadani, M., Nosrati, A., 2019b. Theoretical modelling approaches of heat pipe solar collectors in solar systems: A comprehensive review. Solar Energy 193, 227-243.
Shafieian, A., Khiadani, M., Nosrati, A., 2019c. Thermal performance of an evacuated tube heat pipe solar water heating system in cold season. Applied Thermal Engineering 149, 644-657.
Shafieian, A., Osman, J.J., Khiadani, M., Nosrati, A., 2019d. Enhancing heat pipe solar water heating systems performance using a novel variable mass flow rate technique and different solar working fluids. Solar Energy 186, 191-203.
Taoufik, B., Foued, M., Abdelmajid, J., 2013. Parametric study of a flat plate wick assisted heat pipe solar collector. Journal of Solar Energy Engineering 135(3), 031016.
Yilmaz, C., Koyuncu, I., Alcin, M., Tuna, M., 2019. Artificial Neural Networks based thermodynamic and economic analysis of a hydrogen production system assisted by geothermal energy on Field Programmable Gate Array. International Journal of Hydrogen Energy.

Yılmaz, İ.H., Mwesigye, A., 2018. Modeling, simulation and performance analysis of parabolic trough solar collectors: A comprehensive review. Applied energy 225, 135-174.