INTRODUCTION

Solar energy is the unique type of energy with regard to quantity and environmental points of view. In the past decades, the numerous solar equipment have been designed with novelties and different characteristics. Solar thermal and photovoltaics are the main approaches for solar energy utilization. Photovoltaic-thermal (PV/T) is one of the most leading solar thermal technologies, which provides thermal and electric power simultaneously. Solar irradiation has been employed by thermal and photovoltaic arrangements. A common photovoltaic cell has an efficiency of 4%-17%, while efficiencies higher than 50% can be obtained for thermal applications by solar thermal collectors. However, the state of combination of photovoltaic cells and thermal solar together leads to a variety of different types of PVT systems such as: Air or water-cooled PV/T, glazed and unglazed panels, PVT with natural or forced circulation flow, etc. As a result, various solar thermal collector types have been investigated and examined in the past decade. PVT efficiencies are being improved steadily, whereas the overall performance relies on system configuration and photovoltaic internal-external elements. Several reviews presented latest developments and technologies of flat plate PV/Ts. Also, the prospect and future challenges of PV/T systems are reviewed as well.

Abstract

Renewable energies, specifically solar energy has been employed in numerous applications while being CO₂ emission free energy in comparison with fossil fuel resources. The main purpose of this study is to predict thermal efficiency of photovoltaic-thermal (PV/T) setups in regard with input temperature, recirculation flow rate, and solar irradiation by modifying multilayer perceptron artificial neural network (MLP-ANN), adaptive neuro-fuzzy inference system (ANFIS), and least squares support vector machine (LSSVM) approaches. For this goal, more than 100 empirical measurements were performed on a fabricated water-cooled PV/T setup. Several numerical analyses are also carried out to assess the validity of the presented models. It is confirmed that there is a great agreement between predictive models and actual data. The proposed ANN model provided the best performance due to the mean squared error (MSE) and determination coefficient (R²) values of 0.009 and 1.00, respectively. Also, numerical comparisons with other recently developed models were performed.

KEYWORDS
adaptive neuro-fuzzy inference system, Intelligent models, least squares support vector machine, optimization, MLP-ANN, photovoltaic/Thermal, thermal efficiency

1 | INTRODUCTION

Solar energy is the unique type of energy with regard to quantity and environmental points of view. In the past decades, the numerous solar equipment have been designed with novelties and different characteristics. Solar thermal and photovoltaics are the main approaches for solar energy utilization. Photovoltaic-thermal (PV/T) is one of the most leading solar thermal technologies, which provides thermal and electric power simultaneously. Solar irradiation has been employed by thermal and photovoltaic arrangements. A common photovoltaic cell has an efficiency of 4%-17%, while efficiencies higher than 50% can be obtained for thermal applications by solar thermal collectors. However, the state of combination of photovoltaic cells and thermal solar together leads to a variety of different types of PVT systems such as: Air or water-cooled PV/T, glazed and unglazed panels, PVT with natural or forced circulation flow, etc. As a result, various solar thermal collector types have been investigated and examined in the past decade. PVT efficiencies are being improved steadily, whereas the overall performance relies on system configuration and photovoltaic internal-external elements. Several reviews presented latest developments and technologies of flat plate PV/Ts. Also, the prospect and future challenges of PV/T systems are reviewed as well.
Böer as a leading researcher has built a “Solar One” building in 1973-1974. The aim of air PV/T systems is to maximize the received heat and keep the cell temperature low by the air cooling application. Later in 80s a Hendrie et al. investigated PV/T air heating systems numerically. An unglazed PV/T system was fabricated and studied at the University of Patras. Subsequently, various elements affecting the performance of the system were investigated. A PV/T setup was constructed at Politecnico di Milano, to analyze the operational parameters such as the air flow, collector tilt, and the air gap. Elsafi et al investigated a compound parabolic concentrated (CPC) system experimentally. Additionally, CPC equipped by fins have been modeled and built. An analysis for single and double fan arrangement were performed, as well. Tonui et al investigated the thin flat metallic sheet setup for the collector system. Many studies have performed with the aim of optimum operational conditions analysis of collector and PV/T systems. Some studies have focused on PV/T designs with different radiation area’s and different length to width ratios. A dual channel hybrid PV/T collector was studied numerically. Various PV/T designs have been investigated mathematically by Amori et al in a comparative study. Kumar et al evaluated the air type PV/T systems equipped by air cooling channels.

The water based PV/T setups are the most well-known arrangement among others, whereas the air based models are easier to utilize and have more benefits. Absorbed heat by the collectors could be used for household hot water/air consumption. Applying internal implements in PV/T systems have been investigated in order to enhance the overall efficiency. From the geometric point of view, there are various types of thermal absorber. Allan et al investigated flat plate PV/T systems with 4 absorbing plates: Parallel, Serpentine, Header-Riser, and Bionic. They found that the serpentine cooling is more efficient than Header-Riser. The overall efficiency of Serpentine is about 62% and that of PV/T system using Header-riser is about 59%. Charalambous et al compared PV/T system using serpentine absorber and header-riser in the same conditions. It was reported that the thermal efficiency of the PV/T was 4% more in serpentine that in header-riser prototype. Several PV/T collector designs have been presented due to their significant advantages. Kramer et al have performed an important examination to evaluate PV/T market progress and PV power plants cost analysis.

On the other hand, the artificial intelligence approaches could be expressed as proper cost reduction alternatives. The predictive models are capable to provide output for untrained input elements. An ANN model is applied by Caner et al to provide a significant estimation of solar air collectors efficiency. Also, a predictive model has been presented by Varol and colleagues to predict and evaluate PCM performance in a solar air collectors.

Presently, researchers has focused a great attention on the employment of new computational approaches for detecting the optimum state of the energy systems. Argiriou and colleagues presented a neural controller model for residential hydronic heating plants. The results of experiments showed that the energy could be saved up to 15%. Khatib and colleagues designed a solar irradiation system-based ANN. The results indicated that the model is capable to predict solar irradiation by a mean absolute percentage error (MAPE) of 5.92%, and root mean squared error (RMSE) of 7.96%. Dvorloa and colleagues designed a hybrid ANN system based on Radial Basis Function (RBF) and MLP. The results indicated that RBF configurations are more efficient owing to their lower process power demand, against the MLP. Sulaiman and colleagues designed a hybrid multilayer feed forward neural network (HMLFNN) to predict the power of an on-grid PV system. The designed model employed an artificial immune system to optimize the training procedure as well.

Mellit et al employed an ANFIS utilizing a back propagation learning pattern to estimate the daily PV power system performance. Izgi and colleagues designed an ANN model for a 750 W PV system. Also, the designed model was able to predict hours of high productivity, as well.

Based on the experimental data for fabricated serpentine PV/T system prediction of thermal performance of the system by the mean of multilayer perceptron ANN (MLP-ANN), ANFIS, and LSSVM methods is the main objective of this study.

## 2 | THEORY

### 2.1 | Multilayer perceptron ANN (MLP-ANN)

Artificial neural network is a learning algorithm inspired by natural neural networks of the brain, as a group of interlinked nodes skilled to process exchanged messages within the network. Generally, each node generates an output by the mean of a nonlinear summation of inputs. Also, the parameter of “weight” represents the intensity of the signal changes at an interface. Three major activation functions are as follows:

- **Linear:** \( f(x) = x \)  
- **Sigmoid:** \( f(x) = \frac{1}{1 + e^{-x}} \)  
- **Hyperbolic tangent:** \( f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \)

Furthermore, the bias parameter is also determined as a key element besides the weight parameter. A MLP-ANN is a
feedforward type network with nonlinear activation function. It is noteworthy that the training approach in MLP-ANN is backpropagation algorithm.45,46

2.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The idea of fuzzy logic was presented by Zade for the first time.47 Applying fuzzy logic basics leads to more simple advances and exact result. Employing fuzzy logic and ANN approaches simultaneously provides online learning capability of the ANN and flexibilities of fuzzy logic together.48,49 Employing the fuzzy logic and ANN at the same time, forms the foundation of ANFIS. Fuzzy inference systems have 2 main arrangements: (a) Mamdani, and (b) Takagi- Suga.50-52 Mamdani type, applies logical description for the progress of fuzzy if-then limits, while; Takagi- Sugeno type produces the if-then constrains. The presented if-then laws are used in a general ANFIS arrangement containing 2 input elements:

If $X_1$ is $A_i$ and $X_2$ is $B_i$ then $f_i = m_i X_1 + n_i X_2 + r_i$  

If $X_1$ is $A_2$ and $X_2$ is $B_2$ then $f_2 = m_2 X_1 + n_2 X_2 + r_2$  

If $X_1$ is $A_1$ and $X_2$ is $B_2$ then $f_3 = m_3 X_1 + n_3 X_2 + r_3$  

If $X_1$ is $A_2$ and $X_2$ is $B_1$ then $f_4 = m_4 X_1 + n_4 X_2 + r_4$  

which $A_i$ and $B_i$ ($i = 1,2$) are fuzzy collections for $X_1$ and $X_2$, and $f$ represents the output as well.

Normally, ANFIS configuration contains 5 layers. Equation (8) represent the corresponding Gaussian membership function:

$$O_i = \beta(X) = \exp \left[ -\frac{1}{2} \frac{(X-Z)^2}{\sigma^2} \right]$$  

The Gaussian membership function elements will be set at their optimum values to provide the most exact answers.

The 2nd layer defines the statements’ reliability by the mean of firing strength elements:

$$O_i^2 = w_i = \beta_{A_i}(X) \beta_{B_i}(Y)$$  

The 3rd layer normalizes the obtained firing strength elements:

$$O_i^3 = \bar{w}_i = \frac{w_i}{\sum_i w_i}$$  

The 4th layer processes the linguistic expressions of outputs as follows:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (m_i X_1 + n_i X_2 + r_i)$$  

In the final step, all the output rules are applied together as follows:

$$O_i^5 = \sum_i \bar{w}_i f_i = \sum_i \frac{w_i f_i}{\sum_i w_i}$$  

2.3 Least squares support vector machine (LSSVM)

Support vector machine are controlled learning approaches with correlated learning methods that evaluate data sets for categorizing or regression study. In SVM method, the function is explained as53,54:

$$f(x) = w^T \varphi(x) + b$$  

FIGURE 1 The photovoltaic-thermal (PVT) plate after connecting half-pipe

FIGURE 2 Photovoltaic-thermal (PVT) system during test
By applying the following cost function, values $w$ and $b$ values are obtained:

$$\text{Cost function} = \frac{1}{2}W^T + c \sum_{k=1}^{N} (\xi_k - \xi_k^*)$$  \hspace{1cm} (14)

The lowest amounts of the function are related to the most exact answers. The aforementioned function is corresponding to the following constraints as well:

$$\begin{align*}
    y_k - w^T \varphi(x_k) - b &\leq \xi_k, k = 1, 2, \ldots, N \\
    W^T \varphi(x_k) + b - y_k &\leq \xi_k^*, k = 1, 2, \ldots, N \\
    \xi_k, \xi_k^* &\geq 0
\end{align*}$$  \hspace{1cm} (15)

Suykenes and Vandewalle employed the least squares modification of the SVM approach in order to shorten the solution calculations.\textsuperscript{55,56} They presented a novel cost function as follows:
We have:

\[ Y_k = W^T \varphi(x_k) + b + e_k \]  \hspace{1cm} (17)

The Lagrangian of this problem is determined as:

\[ L(w,b,e,a) = \frac{1}{2} w^T W + \frac{1}{2} \sum_{k=1}^{N} e_k^2 \]  \hspace{1cm} (18)

In order to specify the optimum point of the problem, the saddle point of the Lagrangian should be applied:

\[
\begin{align*}
\frac{dL}{dw} &= 0 \Rightarrow w = \sum_{k=1}^{N} a_k \varphi(x_k) \\
\frac{dL}{db} &= 0 \Rightarrow \sum_{k=1}^{N} a_k = 0 \\
\frac{dL}{da_k} &= 0 \Rightarrow a_k = \gamma, k = 1,2,\ldots,N \\
\frac{dL}{de_k} &= 0 \Rightarrow w^T \varphi(x_k) + b + e_k y_k = 0, k = 1,2,\ldots,N
\end{align*}
\]  \hspace{1cm} (19)

Solving the aforementioned equations will determine the LSSVM characteristics. Along with \( \gamma \), kernel function elements play role as tuning elements as well. The radial basis function is defined as follows:

\[ k(x,x_k) = \exp \left( -\frac{||x-x_k||^2}{\sigma^2} \right) \]  \hspace{1cm} (20)

The variance value should be tuned in radial basis function. Consequently, optimum values of \( \gamma \) and \( \sigma^2 \) should be determined in order to maximize the prediction accuracy:

\[ \text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (H_i^{\text{exp}} - H_i^{\text{cal}})^2 \]  \hspace{1cm} (21)

### 3 | EXPERIMENTAL PROCEDURE AND DATA PREPARATION

Generally, PVT systems include 2 main units: solar cells unit and thermal units. A 90W polycrystalline silicon solar panel with 0.73 m\(^2\) area is used in this study. An aluminum sheet with 3 mm thickness was used as absorber plate that a serpentine tube is connected to this plate (Figure 1).

The panel then connected to a water tank. A tank with a capacity of 100 liters is utilized to handover the heat from PVT setup. Also, an electric water pump is employed for water circulation. Figure 2 illustrates the installed setup during the experiments of this study.
A flowmeter, Pyranometer, solar system power analyzer and 3 thermometers were used as measurement devices for data collection. The water temperatures were measured at 3 points of input, output and midpoint of the tank. The circulation flow rate is regulated by the flowmeter. The solar irradiation is logged by the Pyranometer and operational conditions of photovoltaics, including maximum power, short-circuit current, open circuit voltage, efficiency, etc. are recorded by solar power analyzer.

The tests were done in summer days and at near noon, when the radiation is almost constant and in maximum value. Figure 3 shows the variation in the solar irradiance data that collected during test days.

One of the main parameter that evaluated was the water mass flow rate that changed from 0.5 up to 4 lit/min and other parameter such as the inlet and outlet water temperatures, solar irradiation, electrical specifications of the module such as I-V curve, maximum voltage, current, and power are recorded. Also the effect of inlet temperature of the water is tested. This temperature varied in an interval between 20 to 45°C.
Bubble curve of the thermal efficiency results in different solar radiation and inlet water temperatures is shown in Figure 4. As shown in this figure, the maximum thermal efficiency of 80% has been achieved in lowest inlet water temperature. Also, the diagram shown in Figure 5 represents the investigated parameters variations at different thermal efficiency values. As can be seen, the flowrate ranges between 0.5 and 4 lit/min, the inlet temperature ranges between 21.5 and 46.8°C, solar radiation ranges between 1162 and 1152 watt, and thermal efficiency ranges between 18.56 and 84.4.

Also, the diagram shown in Figure 6 represents the Scatter matrix plot for all measured variables. The scatter diagram depicts the relation of 2 objectives, which is named correlation. It should be noted that the closer the data points become, the greater coherence between variables exists. If the straight line of data points goes from the high values in the y axis to the high values in the x-axis, then the objects are in a negative correlation. As it is shown in Figure 6, due to scattering behavior of variables, the correlations between variables is feeble.
MODELS IMPLEMENTATION

Preprocessing procedure

Three artificial intelligence techniques including MLP-ANN, ANFIS, and LSSVM are used in this investigation in a platform of MATLAB 2016 software, to specify the thermal efficiency as a function of inlet temperature, water flow rate, and solar irradiation. The data set of 100 operational points were used in order to develop the predictive models.

The total dataset consist of 2 subgroups: Train and Test (25% test, 75% train). The training dataset is used for determination of the corresponding elements in the proposed models, whereas the testing dataset validates the results. In order to homogenize data sets, all operational data points were normalized in range of $[-1,+1]$ by the Eq. (22):

$$D_n = 2 \frac{D - D_{\text{min}}}{D_{\text{max}} - D_{\text{min}}} - 1$$  \hspace{1cm} (22)

Thermal efficiency is the output parameter while the other parameters such as inlet temperature, flow rate, and solar radiation) are input parameters of the presented models.

Model development

4.2.1 MLP-ANN

The following equation is used in this investigation for output data set of the designed MLP-ANN:

$$Z = \sum_{i=1}^{n} \left( W_{3i} \frac{1}{1 + e^{-(x_iW_{1i})}} \right) + b_3$$  \hspace{1cm} (23)

ANN arrangement is also trained to define optimized output factors. This goal is attained by regulating weight and bias elements. Error function is presented as follows:

$$E = \sum_{j} \sum_{i} \left( r_{ij} - o_{ij} \right)^2$$  \hspace{1cm} (24)

Optimization procedure is carried out through the Levenberg-Marquardt technique, as well.

The configuration of MLP-ANN is illustrated in Figure 7. Performance of the designed network is presented in Figure 8 on the subject of the MSE calculated for predicted values of the predictive MLP-ANN model.

4.2.2 ANFIS

Schematic structure of a typical ANFIS with double inputs is presented in Figure 9.

Particle swarm optimization (PSO) technique is carried out to train the designed ANFIS model. Total ANFIS parameters number is determined as follows:

$$N_T = N_c \cdot N_v \cdot N_{\text{MF}}$$  \hspace{1cm} (25)

The Gaussian membership function which is employed in this study contains 2 membership function elements of $Z$ and $\sigma^2$. Thermal efficiency, inlet temperature, flow rate, and solar radiation, are implemented variables, and primary number of clusters is set to 5. Consequently, amount of 40 ANFIS elements is provided. RMSE among experimental and predicted values is taken into account as the cost function in PSO process used in determination of the optimal ANFIS elements. Figure 10 depicts the RMSE values for each iteration.

Figure 11 shows the trained membership function for input elements as well.
Least squares support vector machine (LSSVM)-GA chart

**Table 1** Comprehensive information of the 3 designed models

| LSSVM   | Value/comment | ANFIS  | Value/comment | ANN     | Value/comment |
|---------|---------------|--------|---------------|---------|---------------|
| Kernel function | RBF          | Membership Function | Gaussian | Input layer | 3             |
| $\gamma$ | 161098.776177 | MF parameters | 40        | Hidden layer | 5             |
| $\sigma^2$ | 582.561403  | Clusters   | 5          | Output layer | 1             |
| Training data | 75           | Training data | 75        | Hidden layer activation function | Logsig        |
| Testing data | 25           | Testing data | 25        | Output layer activation function | Purelin       |
| Population | 100          | Population  | 50        | Method      | Levenberg-Marquardt |
| Iteration | 1000         | Iteration  | 1000      | Training data | 75             |
| $C_1$    | 1            | $C_1$     | 1          | Testing data | 25             |
| $C_2$    | 2            | $C_2$     | 2          | Max iterations | 1000          |

**4.2.3 | LSSVM**

Least squares support vector machine also uses 2 adaptable elements in its arrangement. These parameters are the regulation parameter ($\gamma$), and the kernel parameter ($\sigma^2$ from the radial basis function formulation). LSSVM method also uses the genetic algorithm (GA) to provide the optimized elements as it is depicted in Figure 12.

**4.3 | Models’ evaluation**

Different statistical indexes (ie MSE, percentage of average relative deviation (ARD%), standard deviation (STD), RMSE, and coefficient of determination ($R^2$)) are used in the evaluation of designed models. Following determinations are presented for the aforementioned indexes:

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (H_i^{exp} - H_i^{cal})^2
\]  
(26)

\[
ARD(\%) = \frac{100}{N} \sum_{i=1}^{N} \frac{|H_i^{exp} - H_i^{cal}|}{H_i^{exp}}
\]  
(27)

\[
STD = \left( \frac{1}{N-1} \sum_{i=1}^{N} (H_i^{exp} - H_i^{cal})^2 \right)^{0.5}
\]  
(28)

\[
RMSE = \left( \frac{1}{N} \sum_{i=1}^{N} (H_i^{exp} - H_i^{cal})^2 \right)^{0.5}
\]  
(29)
RESULTS AND DISCUSSION

Prediction of the thermal performance of PV/T as a function of input water temperature, flow rate, and solar radiation is investigated using 3 approaches (ie MLP-ANN, ANFIS, and LSSVM) using an experimental dataset of 100 data points. Comprehensive information of the 3 designed models (ie MLP-ANN, ANFIS, and LSSVM) are brought in Table 1.

Different numerical methods were used to evaluate the effectiveness and consistency of the designed models. Figure 13 depicts concurrent scheme of experimental for proposed models. As it is shown, among the proposed models; LSSVM model seems to be strongly accurate due to less deviated estimations in comparison with actual values.

Regression results of the are presented in Figure 14. As it is shown, the deviation assessment of all proposed models is presented. LSSVM method seems to have less deviation due to its higher integrated data points near the zero line. Average relative deviations of 0.22, 0.38, and 0.45 are achieved by MLP-ANN, ANFIS, and LSSVM methods, respectively.

\[
R^2 = 1 - \frac{\sum_{i=1}^{N} (H_i^{\text{exp}} - H_i^{\text{cal}})^2}{\sum_{i=1}^{N} (H_i^{\text{exp}} - \bar{H}_{\text{exp}})^2}
\] (30)

5 | RESULTS AND DISCUSSION

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Numerical error analyses are also carried out to evaluate the designed models in training, test and overall sections. The results are presented in Table 2 for all 3 developed models.

5.1 Outlier detection

Mostly, reliability of a proposed model is under the influence of data set which employed for model improvement. Outliers are separate or set of datum/data which behave in contrast with majority of the data set. Hence, recognition and omission of outliers in a data set is essential for achieving higher validities. Leverage examination is carried out to detect possible outliers. By plotting standardized residuals (R) versus hat values (H) the possible outlying will be determined. Diagonal parameters of the hat matrix which are calculated by Equation (31), are the hat values applied in definition of the probability zone:

\[ H = X(X^T X)^{-1} X^T \] (31)

Feasible region is a squared area restricted to cut-off and warning leverage values. Warning leverage value is determined as follows:

\[ H^* = \frac{3k+1}{n} \] (32)

A Cut-off value of 3 is suggested for the standardized residual (R). Feasible region is limited by \( R = \pm 3 \) lines on vertical axis and \( H = 0 \) and \( H = H^* = 0.09 \) on horizontal axis. Outlying data points are those located outside the feasible region. As it is shown in the William’s plot of Figure 16, almost all data are located in the feasible region.

5.2 Sensitivity analysis

Reliance of the goal variable on input elements is strongly specified by the mean of sensitivity analysis. This examination is performed concerning a relevancy parameter (r) varying from −1 to +1. Greater values of r show higher effects of the corresponding element on goal variable. Relevancy factor is determined as follows:

\[ r = \frac{\sum_{i=1}^{N} (X_{ki} - \bar{X}_k)(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N} (X_{ki} - \bar{X}_k)^2 \sum_{i=1}^{N} (y_i - \bar{y})^2}} \] (33)

Relevancy factors of the study are presented in Figure 17. As it is shown, inlet temperature is the most effective parameter on thermal efficiency due to the relevancy factor equal to 0.6.

**TABLE 2** Statistical error analyses for all models

| Model | MSE | RMSE | MRE | \( R^2 \) | STD |
|-------|-----|------|-----|----------|-----|
| LSSVM |     |      |     |          |     |
| Test  | 0.067 | 0.258 | 0.446 | 1.000 | 0.136 |
| Train | 0.072 | 0.268 | 0.373 | 1.000 | 0.184 |
| Total | 0.071 | 0.266 | 0.392 | 1.000 | 0.173 |
| ANFIS |     |      |     |          |     |
| Test  | 0.118 | 0.344 | 0.379 | 0.999 | 0.279 |
| Train | 0.154 | 0.393 | 0.379 | 0.999 | 0.340 |
| Total | 0.145 | 0.381 | 0.379 | 0.999 | 0.324 |
| ANN   |     |      |     |          |     |
| Test  | 0.033 | 0.181 | 0.216 | 1.000 | 0.165 |
| Train | 0.000 | 0.022 | 0.031 | 1.000 | 0.016 |
| Total | 0.009 | 0.093 | 0.076 | 1.000 | 0.087 |
Comparison with other models

Mojumder and colleagues have designed 3 models to estimate the efficiency of PV/T systems utilizing Extreme Learning Machine (ELM), Genetic Programming (GP), and ANN models. Also, Mojumder and colleagues investigated the PV-T thermal efficiency by 3 types of support vector machine method. Table 3 presents numerically comparisons of the presented model in this study and other aforementioned models. As it is shown, our designed models are more accurate than 2 other models, for estimating PV-T thermal performance.

6 | CONCLUSION

Three intelligent algorithms of MLP-ANN, ANFIS, and LSSVM were implemented to constructing a relationship between thermal efficiency of solar collector and inlet temperature, flow rate, and solar radiation. Graphical and statistical methods were employed to determine the credibility of the proposed models in accurate prediction of the thermal efficiency. The proposed ANN model provided the best performance compared to ANFIS and LSSVM models due to the mean squared error (MSE) and determination coefficient ($R^2$) values of 0.009 and 1.00, respectively. Implementation of the outlier detection analysis with the purpose of determining possible outlying data points was also carried out showing the feasibility of the proposed models for majority of data points. Almost all data are located in the feasible region. Sensitivity study was also accomplished to specify effects of different input parameters on
thermal efficiency where inlet temperature revealed the highest impact on thermal efficiency of solar collector regarding higher relevancy factor equal to 0.6. Consequently, these models are user-friendly and can be reliable value in order to investigate effective parameters in solar collectors.

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**How to cite this article:** Zamen M, Baghban A, Pourkiaei SM, Ahmadi MH. Optimization methods using artificial intelligence algorithms to estimate thermal efficiency of PV/T system. *Energy Sci Eng*. 2019;7:821–834. [https://doi.org/10.1002/ese3.312](https://doi.org/10.1002/ese3.312)