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Determination of Effective Parameters on Flat Plate Collector Performance Using Machine Learning Method

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Abstract

In this paper, analytical relationships of flat plate collector absorption rate and solar-to-thermal efficiency are presented. For a sized designed collector without the use of cooling water, the absorber plate stagnation temperature is 132.5 degrees Celsius and by entering the cooling water of one liter per minute, it decreases to 33 degrees Celsius with a collector efficiency of 77%. To predict the collector efficiency, three machine learning models were used: linear, random forest, and decision tree. Seven parameters of solar radiation intensity, collector tilt angle, wind speed, pipe diameter, number of pipes, ambient temperature, and cooling water flow rate, were selected as input parameters. Comparison of the predicted efficiency with actual values showed that the linear model has a weaker evaluation than the other two models. The random forest and the decision tree models perform prediction with almost equal ability and high accuracy (the random forest model predicts negligibly better than the decision tree model). In addition, among the input parameters, changes in collector tilt angle, solar radiation and wind speed insignificantly affects the efficiency. The cooling water flow rate has the greatest effect. The pipe diameter, ambient temperature and the number of the tubes, have a moderate effect.

Keywords: Flat plate collector, Performance, Machine learning, Efficiency, Random forest, Decision tree.

1. Introduction

The global demand for energy is increasing day by day. A large amount of this energy is used to heat water in clinics, homes and industrial processes. Renewable sources can largely replace with fossil fuels to reduce carbon dioxide production and thus bringing clean energy into the life cycle. Of all the renewable energy sources, the availability of solar energy is the highest and has attracted the most attention. A flat plate collector absorbs the radiant energy of the sun and converts it into thermal energy.

A flat plate collector (FPC) consists of an absorber plate, which is usually dark in color and has high absorption ability, and a glass or plastic coating (glaze) on top that transmits solar radiation well and prevents solar energy from returning to the outside with a greenhouse effect. The efficiency and effectiveness of a FPC depend greatly on its location, installation method, dimensions and sizes, radiation coefficients of the absorber plate and the glaze of the collector, the size and number of cooling water pipes, and the heat transfer coefficients of different parts.

The most commonly used configuration is the parallel tube collector, whose thermal performance was investigated by Hottel and Whillier [1]. However, in this type of collector, due to the parallel tube structure, heat loss from the collector increases as a result of the irregular distribution of fluid through the tubes and the temperature distribution of the absorber plate. Colangelo et al. [2] reported the need for low reflection and high transmission of solar radiation while manufacturing different types of FPC solar absorbers. Other methods to increase collector efficiency include: type of tube coating, collector design, installation angle, thermal insulation, integrated collector storage, fluid flow rate, use of phase change materials (PCM) and thermal energy storage [3] as well as installation of twisted strips [4]. In the previous researches, the influence of several thermal parameters such as mass flow rate [5], collector installation angle [6], radiation amount [7], use of nanofluids [8] and use of phase change materials [9], has also been addressed in more detail.

Tailahun [10] stated that since industrial solar thermal systems have erratic, random and flexible behavior, managing the design and analysis of solar systems is a difficult task and therefore researchers use machine learning (ML) method to help in macro-decision making because it allows for multiple versions of one or more modules. Saeed et al. [8] considered different mass flow rates of nanofluid. They developed prediction models using boosted regression tree (BRT) as well as strong gradient boosting (XGBoost). The R^2 values which indicate the improved diagnostic capabilities of the developed models were increased from 0.9619 to 0.9994 by the models built using BRT and from 0.9914 to 0.9997 by the models based on XGBoost. Chandan et al. [11] used a deep computer statistical model to assess the stability of thermal storage systems which was based on property analysis, defect detection, fault diagnosis, life prediction, and state estimation. The simulation results proved that both fewer forecast errors and a higher degree of accuracy were achieved. Compared to alternative techniques, a reduction in the amount of time spent on modeling, evaluations, and instructions was also achieved. Xu et al. [12] developed a simple method for predicting the thermal efficiency of a nanofluid-based FPSC. Machine simulations were used to establish relationships between the efficiencies and the measured heat with the absorbed energy consumption and the collector installation angle. The most suitable tools were developed for prediction of performance of the existing correlations, artificial neural networks (ANN), least squares support vector regression (LS-SVR), and adaptive neuro-fuzzy inference system (ANFIS). These show that the computational accuracy of LS-SVR for evaluating the thermal performance of FPSC is higher than that of other correlations.

Machine learning models used for FPCs are trained to predict thermal parameters in a geographical location and can be generalized to other regions with different climatic conditions. Machine learning can help predict outcomes or trends. In addition, machine learning techniques can automate tasks and save time and resources. Ultimately, the use of machine learning increases the accuracy, efficiency, and depth of analysis, leading to more robust findings.

In the present study, a comprehensive thermal analysis of a FPC is carried out and the collector efficiency and its outlet water temperature are determined in terms of other parameters. The heat transfer coefficient between the absorber plate and the glaze is calculated accurately. This analytical method creates a comprehensive and valid dataset for use in the machine learning method. A simple linear method is used alongside two more accurate methods of decision tree and random forest, and their results are compared. Here, parameters that are under the direct control of the designer have been selected as input parameters and their percentage effect on the collector efficiency is obtained.

2. Methodology

Figure (1) shows a Flat Plate Collector (FPC) that is tilted at an angle to the horizon. The cooling water pipes are installed under the absorber plate from bottom to top along the length of the collector. The absorber plate receives solar energy after passing through a glass cover; part of it is lost to the environment and the rest which is useful heat is transferred to the cooling water and warm it. Table (1) gives the FPC specifications.

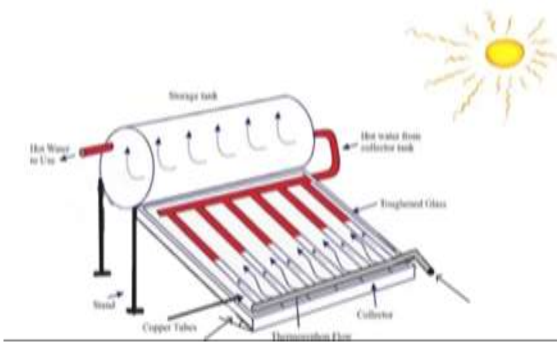

Figure 1. Flat plate collector with tilt angle

Table 1. Flat plate collector specifications

Parameter	Value
Solar irradiance	800 (W/m^2)
Tilt angle	45 (degree)
Cooling water inlet temp.	15 (^{o}C)
Collector length	2 m
Glaze transmissivity	0.8
Absorber absorptivity	0.9
Cooling water mass flowrate	1 (lit/min)
Absorber emissivity	0.95
Glaze emissivity	0.88
Ambient temperature	25 (^{o}C)
Wind speed	5 (m/s)
Gap thickness (absorber-glaze)	15 (cm)
Cooling water tube diameter	6 (cm)
Number of tubes	6

3. Discussion and Results

The FPC stagnation temperature (T_{st}) is the absorber plate temperature in a state where the energy absorbed by the absorber plate is not transferred to the cooling water and all of that energy is lost in exchange with the environment, then, the temperature of the absorber plate reaches its highest value. With the design parameters, it is equal to 132.5 ^{o}C. Figure (2) shows FPC thermal efficiency (η), absorber plate temperature (T_p), and cooling water outlet temperature (T_{fo}), with increasing of cooling water flowrate in range of 0 to 1.2 lit/min.

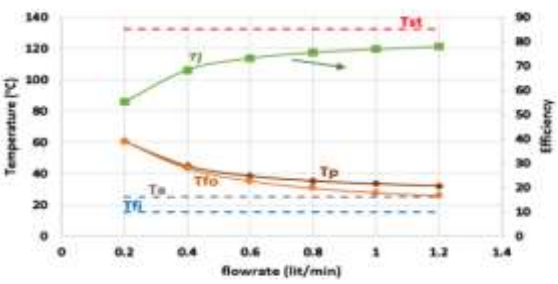

Figure 2. FPC temperatures with water cooling rate

Machine Learning for FPC

The most main parameters of a flat-plate collector ensure optimal performance (the best collector efficiency as output) within specific ranges are selected as inputs to the machine learning. Those are: Solar radiation intensity (I_T), Collector tilt angle (β), Wind speed (V_W), Tube diameter (d), Number of tubes (n), Ambient temperature (T_a), and Cooling water flow rate (ṁ). Table 2 presents the acceptable ranges for the seven input parameters.

Table 2. FPC parameter ranges (ML inputs)

Parameter	Range
Solar irradiance	600, 800, 1000, 1200 (W/m^2)
Tilt angle	15, 30, 45, 60, 75 (degree)
Wind speed	0, 5, 10, 15 (m/s)
Tube diameter	6, 8, 10 (cm)
Number of tubes	6, 8, 10
Ambient temperature	15, 20, 25, 30, 35 (^{o}C)
Cooling water mass flowrate	0.2,0.4,0.6,0.8,1,1.2 (lit/min)

Regression accuracy can be measured using the Mean Squared Error (MSE) parameter. This parameter represents the average of the squared differences between predicted and real values, serving as an assessment of how closely a model predictions align with reality. A lower MSE value indicates a better predictive model.

$$MSE = (\frac{1}{n}) \sum (predicted\ value - actual\ value)^2 \quad (1)$$

here, n is the number of parameters used in the regression.
R^2 represents the percentage of output variability explained by the inputs. The closer the its value to one, the better the model is accounting for the data.

$$R^2 = 1 - \frac{SSR}{SST} = \frac{\sum(actual\ value - predicted\ value)^2}{\sum(actual\ value - actuals\ mean)^2} \quad (2)$$

Mean Absolute Error (MAE) is a regression metric for measuring error that considers the average of the absolute differences between model predictions and the real data across the entire dataset. Unlike MSE, MAE does not assign excessive weight to invalid data points.

$$MAE = (\frac{1}{n}) \sum |predicted\ value - actual\ value| \quad (3)$$

RMSE provides an estimate of the average deviation of predicted values from real values within a dataset. In machine learning, having a unique parameter during training, cross-validation, and post monitoring, is highly useful.

$$RMSE = \sqrt{\frac{\sum(predicted\ value - actual\ valu)^2}{n}} \quad (4)$$

Multiple Linear Regression is a simple machine learning method that is used with multiple inputs.

Decision Tree Regression is a nonlinear method widely used in machine learning. Unlike linear regression, decision trees partition the feature space in a hierarchical, rule-based manner, enabling them to capture complex, nonlinear relationships. The model iteratively splits the data into subsets based on features that minimize prediction error, thereby forming a tree-like structure. This structure allows the model to capture nonlinearities by focusing on error minimization through successive splits. With the decision tree model, the evaluation metrics differ significantly from those of the linear model.

Random Forest Regression is a widely used machine learning algorithm that combines the outputs of multiple decision trees to arrive at a single result. The method simplicity for use and flexibility, combined with its effectiveness, have contributed to its growing popularity. The general random forest method employs a random decision tree algorithm to construct multiple trees and subsequently combines them. Forests composed of trees split by oblique hyperplanes can achieve higher accuracy as they grow without suffering from overfitting provided that the forests are randomly constrained to respond only to a subset of selected feature dimensions. Predictions made by the random forest method are closer to the real values than those of the two previous models. The evaluation metrics are compared in Table 3 for all three models. Figure 3 shows the effect of inputs on collector efficiency (by percent).

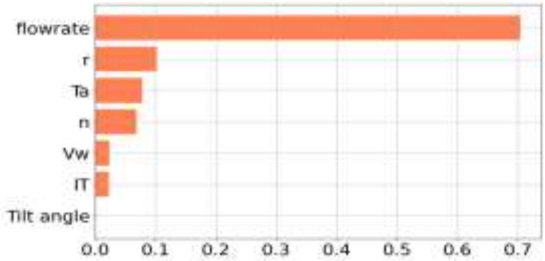

Figure 3. Comparison of inputs on FPC efficiency (by percent) in randon forest model

Table 3. Metric comparison of the three ML models

Model	*MSE*	R^2	*MAE*	*RMSE*
Linear	23.232777	0.849277	4.058011	4.820039
Decision tree	0.073191	0.999525	0.199172	0.270538
Random forest	0.049623	0.999678	0.15825	0.222761

4. Conclusion

In the present study, the analytical relationships and governing principles regarding the absorption rate and solar-to-thermal conversion efficiency of a flat-plate collector were first established in detail. For a sized design collector, the stagnation temperature was 132.5°C for zero cooling water flow rate. As the cooling water flow rate increases, the absorber plate temperature drops and the collector efficiency rises; specifically, at a flow rate of 1 liter per minute, the absorber plate temperature reaches 33°C and the collector efficiency reaches 77%.

To predict collector efficiency using machine learning, three models were employed: linear regression, decision tree, and random forest. Seven parameters were selected as inputs: solar radiation intensity, collector tilt angle, wind speed, tube diameter, number of tubes, ambient temperature, and cooling water mass flow rate.

The values of the evaluation metrics are compared in Table 3. It shows that the linear model performed less effectively than the other two models. The decision tree and random forest models demonstrated high predictive accuracy with nearly identical capabilities (with the random forest model showing marginally higher accuracy than the decision tree model).

Furthermore, among the input parameters, the installation angle, wind speed, and solar radiation have a negligible impact on efficiency. The cooling water flow rate exerts the greatest influence. Three parameters of the number of tubes, ambient temperature, and tube diameter have a low-to-moderate impact with their effects being roughly equivalent.

The future work can be constructing a laboratory setup of this collector. The data obtained from it will then be used to calibrate the machine learning model against experimental data.

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