International Journal of Scientific Research in Computer Science, Engineering and Information Technology
ISSN : 2456-3307 (www.ijsrcseit.com)
doi : https://doi.org/10.32628/IJSRCSEIT

Predicting The Performance of Solar Collector Using Advanced Clustering with Artificial Neutral Networking

[1]Richika Kumari, [2]Harsh Mathur

Author[1] PG Research Scholar, Author[2] Assistant Professor
Department of Computer Science Engineering, Rabindranath Tagore University, Bhopal, Madhya Pradesh, India

ARTICLEINFO

Article History:

Accepted: 01 Nov 2022
Published: 23 Nov 2022

Publication Issue
Volume 8, Issue 6
November-December-2022

Page Number
667-676

ABSTRACT

In the present study three different types of neural models: multi-layer perceptron (MLP), has been used to predict the exergetic efficiency of roughened solar air heater. The operation of a flat-plate solar collector using water as a working fluid flows (water, i.e. 1 L/min) has been modelled using the artificial neural networks (ANNs) of computational intelligence technique. The ANNs model has been built at the entrance to predict the outlet temperature in the flat-plate solar collector using measured data of solar irradiance, ambient temperature, inlet temperature and working fluid flowA novel all-glass straight-through tube solar collector is employed as reference solar technology. In the present approach, experimental collector performance data was first collected during different weather conditions (sunny, cloudy, rainy days) subject to a clustering analysis to screen out outlier samples. The data was then used to train and verify the neural network models. For the ANN, the Back Propagation (BP) and Convolutional Neural Network (CNN) models were used. For predicting the performance (thermal efficiency) of the solar collector, solar radiation intensity, ambient temperature, wind speed, fluid flow rate, and fluid inlet temperature were used as the input parameters in the model. The prediction accuracy of the neural network models after full-data-screening were superior to that of the pre-screening and partial-screening models. The CNN model provided somewhat better efficiency predictions than the BP model. The R2, RMSE and MAE of the CNN model prediction in sunny conditions with full-screening was 0.9693, 0.0039 and 0.0030, respectively. The average MAPE of the BP and CNN models for all three weather types dropped by 30.7% and 13.8%, respectively, when applying data pre-screening and partial-screening only. The accuracy of the ANN collector prediction model can thus be improved through data clustering, which provides an effective method for performance prediction of solar collectors.

Keywords: ANN, Solar Collector, Performance, Predicting, MLP.

I. INTRODUCTION

The ANN method is very famous in the area of thermal system in the last twenty years. The consumption of energy is increased in day-by-day life. The main aim of researchers are effective way to utilize the available energy. Various researchers used of ANN technique for modeling and prediction of thermal performance of solar system. There has been various work related to Artificial neutral networking.

Maind and Wankar [1] studied the comparative analysis of computational technique using experimental and analytic method. It found that this technique is an accurate and time saving for complex problem. The use of Artificial Neural Networks (ANN), on the other hand, saves time and provides key information patterns in a multi-dimensional information domain and, therefore, this technique has been becoming increasingly popular in Science and Engineering sectors. In recent years, many researchers have used ANN in solar collector systems [2-3]. Caner et al. [4] and Benli [5] specially applied ANN model to predict the performance of different types of SAH. Facao et al. [6] constructed two different types of NN model by use of MLP and RBF, and predicted the collector efficiency and useful heat gain of plate and tube type heat pipe hybrid solar collector. They also found that MLP model performed slightly better than RBFs model. Islamoglu et al. [7] applied neural technique to predict the heat transfer analysis of corrugated channel. They conducted experiments and collected data for ANN modeling. They found the results of predicted data with actual experimental data less than 4% error of MAE.

Sozen et al. [8] conducted experiments on flat plate solar air heater and calculated the thermal efficiency. By the use of experimental and calculated data, optimal ANN was constructed using seven parameters in input layer, twenty neurons with two hidden layers and one neuron used in output layer and predicted the thermal efficiency with satisfactory results. Akdag et al. [9] structured ANN model to predict the heat transfer in oscillating annular flow. They found the predicted results with less than 5 % error.

Kalogirou et al. [10] studied the performance of solar steam generator using ANN technique with parabolic collector. They found that the predicted results with the maximum deviation 3.9 %. Kalogirou et al. [11] analyzed the performance of domestic solar water heater proposed by ANN model. They concluded that the ANN model trained with collected data and predicted data were 7.1% and 9.7% respectively. Kalogirou et al. [12] developed the performance of thermo-siphon solar water heating system with ANN model. For this work, they collected 54 data sets, in which 46 were used for training and rest of 8 used for testing. They predicted results with maximum deviations 1 MJ and 2.2 °C for two output parameters. Kalogirou [13] studied the performance of solar water heater with forced circulation using ANN model to predict. For this work, they created two types of ANN model through 13-5-1 and 14-7-2 neural model. It found that the maximum deviations were 1.9% and 5.5% for the two ANN models. Farkas et al. [14] analyzed the performance of flat plate solar collector using ANN technique. The ANN model was created with three input constraints, such as solar intensity, ambient temperature and inlet air temperature, and in output layer single parameter with outlet temperature of air. It has been found that the overall deviation in outlet temperature of solar collector was 0.9 °C. Cetiner et al. [15] analyzed the performances of solar collector with ANN technique. For this work, they built experimental setup and collected data for study. Total 32 data were collected, from which 26 were used for training and rest of 6 used for testing. They developed ANN model with four parameters in input layer and three parameters in output layer, and in hidden layer 7 numbers of neurons found to be optimal number. For training of 4-7-3 neural model LM learning algorithm was used and predicted results with less error.

Lecoeuche and Lalot [16] studied the performance of solar collectors using ANN model. They developed two models: single input single output (SISO) and multiple input single output (MISO). The solar radiation was input data and outlet air temperature was output data using SISO model. The solar radiation and thermal heat loss coefficient were input data and outlet temperature of air was taken as an output data using MISO model.

Sozen et al. [17] introduced the thermal performance of flat plate solar collectors using ANN technique. The Seven factors such as experimental date, time, absorber surface temperature, solar radiation intensity, declination angle, tilt angle and azimuth angle were selected as input data. The efficiency of the collector was taken as output parameter. It has been found that the maximum and minimum deviations of results were 2.558484 and 0.001969, respectively.

Aly et al. [18] studied the performance of open-cycle solar collector with ANN model. It found that the predicted with minimum error and maximum values of correlation coefficients (R2).

Caner et al. [19] introduced the performance solar air collector using ANN tool. It conducted experiments on the basis of two different types of absorber plate: zigzagged and flat plate. Total 80 data sets were collected from the experiments. The ANN tool was created with MLP 8-20-1. In which 8 parameters were used in input layer, such as absorber model type, time of experiments, outlet and inlet temperature of air, stored water temperature, ambient and absorber surface temperature, and solar intensity. Efficiency of the system was nominated as output parameters. The value of MAE, SSE, RMSE, MRE and R2 were found to be 0.9879, 0.0239, 1.73, 3.0671 and 0.9967 respectively, which gives the satisfactory performance of neural mode.

Cakmak and Yildiz [20] developed feed forward neural network (FFNN) to predict the seedy grape drying rate using solar air collector. The optimal ANN model constructed with 3-10-1 neurons for predicting results. They compared among different model like FNN, NLR and MLR model. It found that the FNN model as the best model as compared to NLR and MLR model.

Fisher et al. [21] studied the performance of two types of solar collectors. It constructed two types of model 5-5-1 and 5-4-1 neural model for conventional flat plate collector and an evacuated tubular collector respectively. The results revealed that the satisfactory performance of ANN model with the state-of-the-art modeling.

Kamthania et al. [22] introduced the performance of hybrid PV/T double pass air collector using ANN technique. They collected Data from five stations (Bangalore, Mumbai, Srinagar, Jodhpur and Delhi). In input layer, global solar radiation, ambient temperature, diffuse radiation and number of clear days were used. In output layer, electrical energy, thermal energy, overall exergy, and overall thermal energy were used. LM with 15 neurons was selected in hidden layer. Finally 4–15-4 optimal model successfully predicted data. The RMSE values for electrical, thermal, overall thermal energy and overall exergy has been found varying from 0.10% to 1.63%, 0.93–1.86%, 0.59–2.23% and 0.319–1.12%, respectively.

The objective of this works, the prediction presented in the ANNs models and that there is very limited work related to prediction of solar collector model using three different mass flow rate of fluids. In present work, total fifty sample data sets are used which are obtained from experiments for solar collector using three different mass flow rate and the sample data divided into three groups as training (80% data), validation (10% data) and testing (10% data). The optimal ANN model has been found by statistical error analysis of training stage. The proposed MLP ANN model predicted results have been compared with actual experimental data. Predicted and measured values of thermal efficiencies have been compared.

II. MATERIALS AND METHODS

2.1 Experimental Study and Data Collection

In this study, 96 data sample have been used which is collected from experimental study of unidirectional flow wire mesh SAH [6]. These samples are measured for 12 days, in which 48 samples are for each of porous absorber type A and type B.

The detailed specifications of solar water collectors are described in Table 1. Type-I named as corrugated solar air collector, type-II named as trapeze solar air collector. The air flow is provided as seen in Fig. 1. Experiments are carried out between 09.00 and 17.00 on October 15, 2009 under Elazıgˇ weather conditions (38:41_N latitude; 39:14_E longitude). Two collectors were placed facing south and a slope angle of 37 with the respect to horizontal line. Each of the two collectors had 0.7 m width and 1.7 m length. The collection surfaces area of solar radiation were 1.8663 m2 in type-I, 1.3125 m2 in type-II. The absorbing surfaces in two collectors were formed by a dull black painted galvanized sheet with 0.4 mm thick. A single glazing of 4 mm glass was used in two collectors. In order to minimize energy losses from the bottom of the collectors, all collectors had the backs and sides insulated with a 70 and 50 mm of glass wool insulation, respectively. During the experiments, the inlet and outlet air temperatures of the solar air collector, mass flow rate of air, ambient temperature, surface temperature of collectors and solar radiation density are measured.

The experiments were conducted from September 2009 to December 2009. The experiments were carried out at the same time periods between 9.00 and 17.00 of the days for a variety of mass flow rates. The flow rate was kept constant for both collectors. The experiments were carried out for m_ ¼ 0:036 kg s_1 mass flow rate.

The air flow was provided by a centrifugal fan 0.75 kW and 1500 rpm. The air flow rate was measured by a flow meters placed at the outlet of the collectors in a vertical position. The intensity of incident solar radiation was measured by means of a Pyranometer, connected to a digital micro voltmeter for direct display. Copper–Constantan thermocouples (28 SWG) were used to measure the air temperatures at inlet and outlet of the test sections and the ambient temperature. The measurement of air flow rate through the test section has been accomplished by using orifice meters.

The data were collected for the parameters: mass flow rate, wind speed, atmospheric air temperature, inlet air temperature, outlet air temperature, mean air temperature and solar intensity in the open sky days for at interval of 30 min.

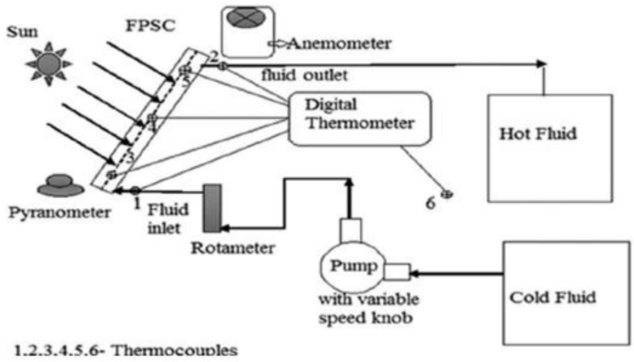

Figure 1. Schematic diagram of the experimental setup. (Pathak et al. 2019)

2.2 Artificial neural network (ANN)

ANNs method is used for modeling, optimization, simulation and forecast of performance of a system. ANNs technique is a data processing systems related to that of human brain data processing information. ANNs model consists of multiple inputs, multiple output and hidden layer.

2.2.1 Multi-layer Perception

The most commonly used neural model for prediction is MLP, which consists of three layers: First input layer, last output layer and in middle hidden layer. In feed forward networks, each product of inputelements (ai) and weights (wij) are fed to summing junctions and is summed with bias (bj) of neurons as follows ((Kalogirou, 2000; Haykin,1994):

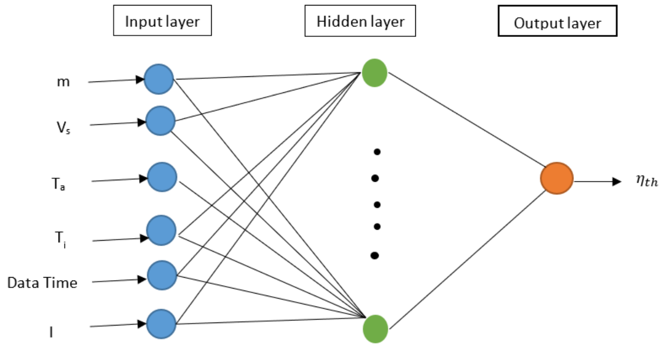

Fig. 2 MLP model of present work

In this study, first we select the number of data's which depends on the performance of solar water collector. The three layer of network structure is shown in figure.

Six input variables are mass flow rate of water(m), wind speed (V), ambient temperature (T_a), inlet water temperature, data time and solar radiation (I) respectively. These six input variables are obtained from experimental studies and one output variable is the performance of solar water collector. The main objective of MLP model is to predict the performance of solar water collector by using input and output data sets.

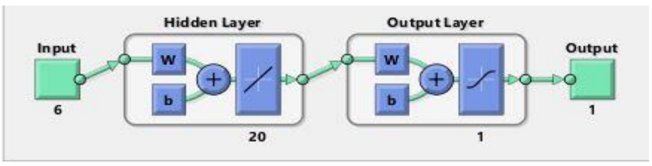

Fig.3 Simple neutral network of present model

Thus MLP with the neuron numbers (6, 20, 1) is set up in this paper. It is most widely used type of neural network.

2.2.2 Clustering analysis

In actual condition the weather will vary over time affecting the performance of the collector, also causing uncertainty in the measurement data. This leads to some outlier data which differ from the data in a normal situation. These sample data points are far from the main data set, forming outliers. In this study, they are defined as "invalid samples". Clustering analysis helps to screen the original data and eliminate the invalid samples. Italso decreases the degree of data dispersion and improves the accuracy of the prediction.

2.2.3 Back Propagation neural Network

The Back Propagation neural network (BP) is the most common neural network model available and is used as a benchmark for comparing prediction performance. BP is a kind of multi-layer feedforward neural network with error back-propagation (Zhang et al., 2019a; Wang et al., 2011; Jiang, 2009), which is composed of signal forward transmission and error back-propagation. BP consists input, hidden, and output layers. The input signal is transmitted to each hidden layer through the input layer, and finally to the output layer.

2.2.4 CNN (Convolutional Neural Network)

The CNN contains convolution, pooling and fully connected layers (Wang et al., 2019; Zhang et al., 2019b; Gu et al., 2018), as illustrated in Fig. 5. Usually there is a convolution layer after the input layer and a pooling layer after the convolution layer. The combination can be repeated many times to increase the depth of the CNN.The input layer of the convolutional neural network usually processes multidimensional data. The convolutional layer aims to extract the features of input data. It contains several convolution kernels, and each element of the convolution kernel corresponds to a weight coefficient and a bias. Each neuron in the convolution layer is connected to multiple neurons in a close region in the previous layer, which is called the receptive field. When convolution kernel works, it scans the receptive field and the input features are summed by multiplication of matrix elements and the bias is added.The Convolutional Neural Network (CNN) has seldom been applied to solar energy.

2.2.5 Data Normalization

Data normalization is a basic process in data mining. Different evaluation indexes often have different dimensions and dimensional units, which will affect the results of the data analysis. In order to eliminate the dimensional influence among the indices, data normalization is essential to solve the comparability among the data indices. After data normalization, each index is in the same order of magnitude, which is suitable for comparative evaluation. In this work, data normalization was done as follows (Ghritlahre and Prasad, 2018a,c; Sozenm et al., 2008):

2.2.6 Performance Criteria

The prediction performance evaluation of the neural network models is done on the basis of R2, RMSE, MAE and MAPE (Ghritlahre and Prasad, 2018a; Shafieian et al., 2020; Hu et al., 2016; Qureshi et al., 2017) explained in the next: Coefficient of Determination: where n is the total number of data, XA,i is the actual thermal efficiency of the solar collector, and Xp,I is the predicted efficiency value. From Eq. (16), the lower the MAPE, the better the prediction accuracy of the model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_{p,i} - X_i)^2}$$

Where $X_{p,i}$ is the forecasted value and X_i is the measured value.

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left|(X_{p,i} - X_i)\right|$$

$$R^2 = \left(1 - \left(\frac{\sum_{i=1}^{n}\left|(X_{p,i} - X_i)^2\right|}{\sum^{n} X_i}\right)\right)$$

III. RESULTS AND DISCUSSION

This section introduces concise information about the experimental database, the pre-processing calculations, and the procedure of finding the best architecture of each AI-based model. Finally, the best AI model was validated with a reliable empirical model and then employed to analyse the thermal performance of flat plate solar cells.

Table 1 : Statics of screening weather BP neural Network Model

	Weather type	Sunny	Cloudy	Rainy	Average
Case 1 (Unscreened)	R	0.821	0.762	0.731	0.771333
	RMSE	0.007	0.012	0.001	0.006667
	MAE	0.005	0.008	0.002	0.005
Case 1 (Partially screening)	R	0.844	0.841	0.818	0.834333
	RMSE	0.006	0.001	0.828	0.278333
	MAE	0.003	0.007	0.002	0.004
Case 3 full screening	R	0.941	0.800	0.844	0.861667
	RMSE	0.004	0.007	0.011	0.007333
	MAE	0.002	0.006	0.013	0.007

Table 2 : Statics of screening weather **CNN** neural Network Model

	Weather type	Sunny	Cloudy	Rainy	Average
Case 1 (Unscreened)	R	0.851	0.882	0.741	0.824667
	RMSE	0.008	0.013	0.010	0.010333
	MAE	0.007	0.010	0.021	0.012667
Case 1 (Partially screening)	R	0.908	0.852	0.881	0.880333
	RMSE	0.006	0.010	0.828	0.281333
	MAE	0.003	0.009	0.020	0.010667
Case 3 full screening	R	0.952	0.810	0.858	0.873333
	RMSE	0.006	0.005	0.020	0.010333
	MAE	0.002	0.006	0.013	0.007

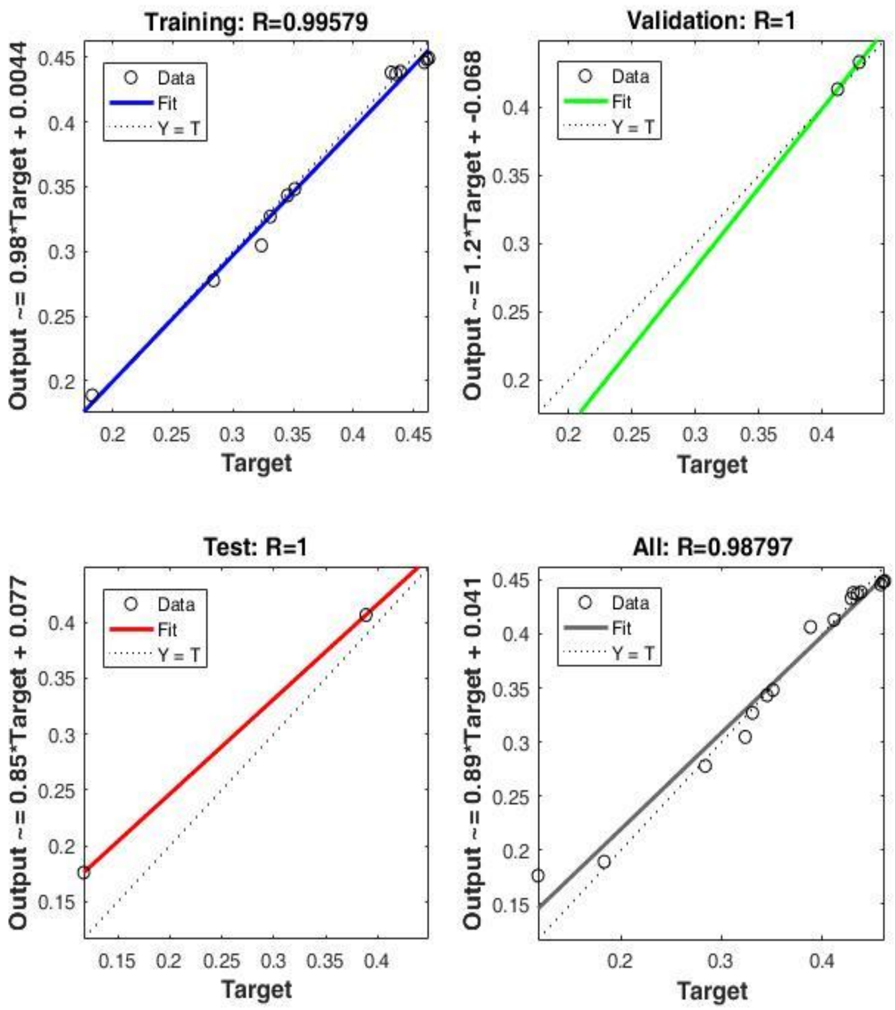

Fig. 4. Regression analysis with training, validation, test and all data.

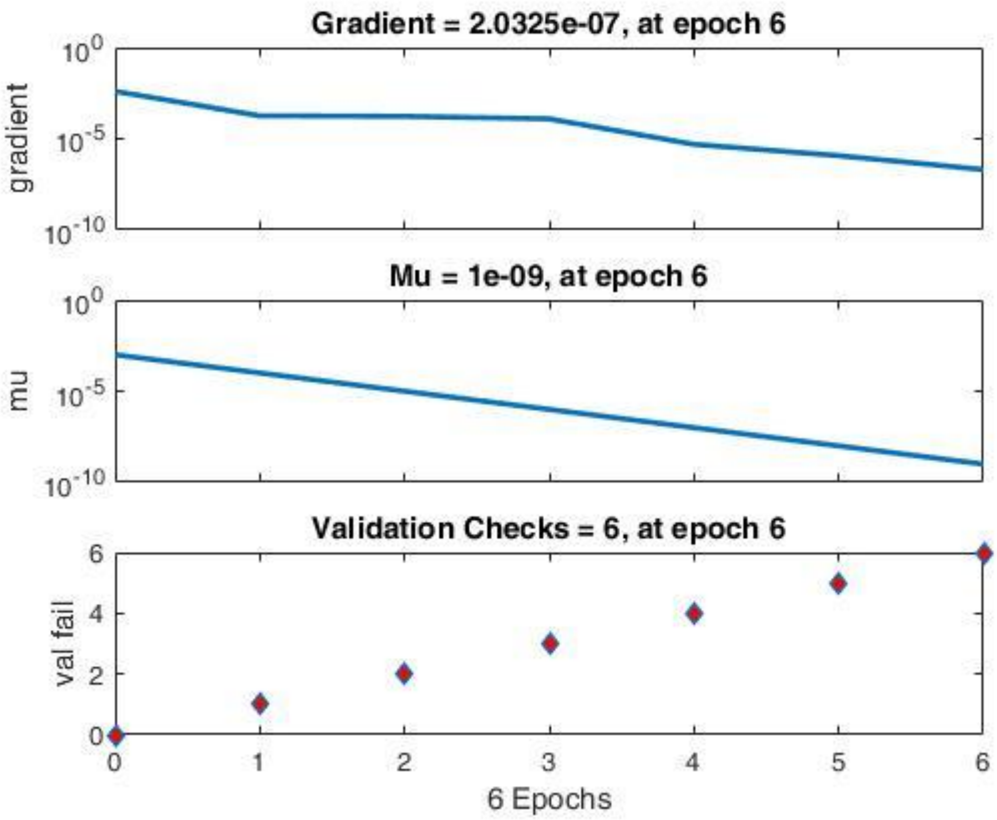

Fig. 5. Variation of the gradient error, l and validation error.

In Fig. 5, the dashed line is the perfect fit line where outputs and targets are equal to each other. The circles are the data points and colored line represents the best fit between outputs and targets. Here it is important to note that circles gather across the dashed line, so our outputs are not far from their targets. According to these results we can say that used MLP structure of ANN is very well to predict performance of the two type solar air collectors. Variation of the gradient error, value of l and validation error are shown in Fig. 6. Also stopping of training process is shown due to reaching minimum gradient error at epoch 6.

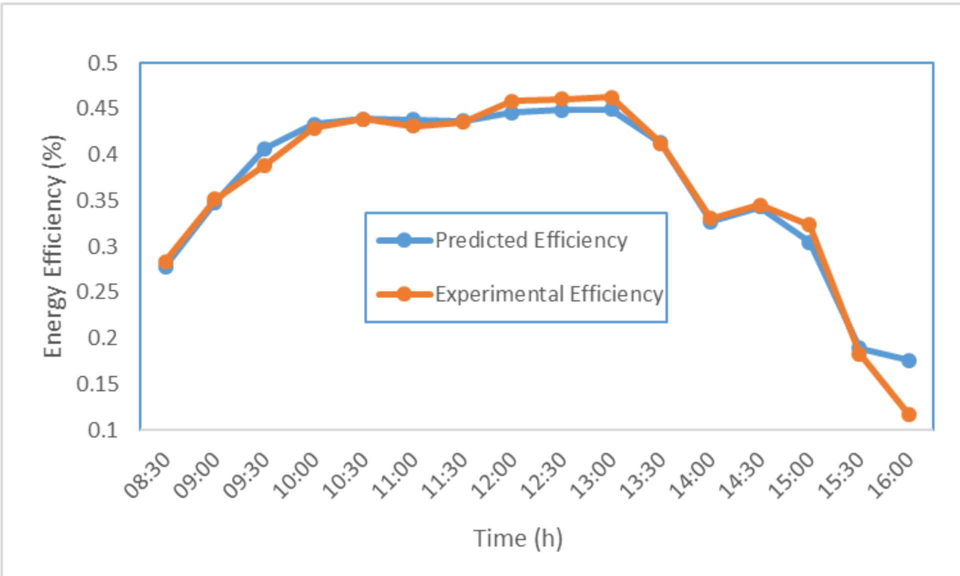

Fig. 6. Comparison between Predicted and experimental thermal performance

IV. CONCLUSION

The Artificial Neural Networks (ANN) technique has also been applied to predict the performance of solar collector. The ANN structure has been constructed with MLP model, using seven parameters in input layer and one parameter in output layer. The experimental results have been compared with those of ANN predicted values. On basis of the experimetal results and ANN predicted results, the following conclusions have been drawn: he result of the ANN model is accurate and satisfactory with the experimental data. A larger database inputs used as training sets of data in neural network model may further improve the predictions. The ANN model developed can predict fast and accurate results of thermal efficiency of porous bed solar air heater. ANN technique can be used in several engineering applications as it provides better, quick and more realistic results without the need of conducting series of tests for a long time.

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Cite this article as :

Richika Kumari, Harsh Mathur , "Predicting The Performance of Solar Collector Using Advanced Clustering with Artificial Neutral Networking", International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN : 2456-3307, Volume 8, Issue 6, pp.667-676, November-December-2022.