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Performance Prediction of Flat-Plate Solar Collectors Using MLP and ANFIS

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ABSTRACT

Efficiency is playing a crucial role in designing solar energy systems. The objective of this paper is based on multi-layer perceptron (MLP) and adaptive neuro fuzzy interface system (ANFIS) to model and predict the efficiency of flat-plate solar collectors. The Levenberg-Marquardt learning algorithm and logistic sigmoid transfer function are used in the MLP. Tehran meteorological data is used as the training data in order to train the neural network. Solar irradiance, ambient temperature, collector tilt angle and working fluid mass flow rate are used in the input layer of the network and the efficiency is presented at the output layer. The results have shown that the MLP with (14,7,1) neurons in network layers structure and ANFIS with sixty-two clusters give the most suitable algorithm with minimum root mean square error (RMSE), maximum correlation coefficient (R^2) and low mean bias error (MBE). The advantages of Artificial Neural Network (ANN) models compared to the conventional testing methods are speed, simplicity, and high capacity to learn from examples. The best result belongs to the ANFIS model with R^2= 0.995, RMSE= 0.047 and MBE= 0.0001.
KEYWORDS: Solar collector, MLP (Multi-layer Perceptron), ANFIS (Adaptive Neuro Fuzzy Inference System) Collector Efficiency.

1. INTRODUCTION

There has been an increasing interest in research and development of renewable energy in recent two decades, due to the limited fossil fuels resources and the harmful utilization of these fuels for the environment. Scientific developments in the field of solar collectors and solar water heaters have grown substantially in recent. In order to make better use of solar systems, solar collector's efficiency is determined by various tests in different conditions. This is done while the tests require advanced equipment and high cost facilities. With these limitations, the researchers tried to determine the efficiency of solar collectors by modeling these systems. For this purpose various relations have been introduced which are not accurate enough in addition to their complexity. In recent years, numerous studies have been conducted for predicting solar collector efficiency and to optimize the effective collector parameters by using artificial intelligence techniques.

Kalogirou et al. had employed a neural network for modeling a domestic water heating system(1999) [1]. Farkas et al. (2003) [2] have developed an ANN model to determine the output temperature and the performance of flat plate solar collector. They used the inlet and outlet fluid temperature as input and output parameters, respectively(Farkas and Geczy-Vıg, 2003). Kalogirou (2006) [3] applied Artificial Neural Network to predict the performance of flat plate collector Sozan et al. (2008) [4] used ANN to specify the performance of flat plate collector by using meteorological parameters.

Hui Xie (2009) [5] proposed a new ANN-based model to estimate the solar collector performance. They used ambient temperature, solar angles (azimuth and declination angles) and tilt angle as input and the performance of collector and heat capacity as output of the network. Tariq et al. (2012) [6] investigated a solar water heater consists of a flat plate collector and four water reservoirs by using ANN.

In this paper MLP (Multi-Layer Perceptron) and ANFIS (Adaptive Neuro Fuzzy Inference System) methods are used to predict the efficiency of flat-plate solar collectors. Results show that these methods can be used to determine collector efficiency instead of time consuming actual tests, with an acceptable accuracy.

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2. MATERIAL AND METHOD

The data is gathered from solar collector's test station and meteorological weather station located in Islamic Azad University, South Tehran Branch, Tehran (35_41N, 51_19E), Iran. *Fig. 1* shows a picture of the test facility. Details of the system can be found in Jafarkazemi et. al. (2011) [7].

Fig.1. Collector test facility used for testing the collectors.

The data are normalized to values between 0 and 1 for the consistency of network learning as well as degradation in computation time via the following equation:

$$f(x) = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Where f(x) and x indicate normalized and actual values respectively. The data was divided into three groups. Regarding the utilized data of the current study, 143 data sets are used to train RNN and ANFIS, 30 data sets for testing and 31 data sets are used for the purpose of models validation. It is remarkable that the utilized data to test the performance of the trained network have been apart from training and validation dataset. Test data was randomly selected and wasn't used in training and validation process. To compare performance of the models general statistical indicators such as root mean square error (RMSE), mean bias error (MBE) and correlation coefficient (R^2) are applied with the actual and the output data of the trained networks. In this regard, test dataset are considered as the input.

The equations regarding the utilized statistical indicators are given as follows:

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

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

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left|(X_{p,i} - X_i)\right| \tag{3}$$

$$R^2 = \left(1 - \left(\frac{\sum_{i=1}^{n}\left|(X_{p,i} - X_i)^2\right|}{\sum_{i=1}^{n} X_i}\right)\right) \tag{4}$$

2.1. Mathematical basis of ANFIS

ANFIS is a multilayer feed-forward network which uses neural network learning algorithms and fuzzy reasoning simultaneously to learn rules from input data. The ANFIS architecture of a first-order Sugeno fuzzy model with two rules is shown in *Fig. 2* (Anon., 2013) [8].

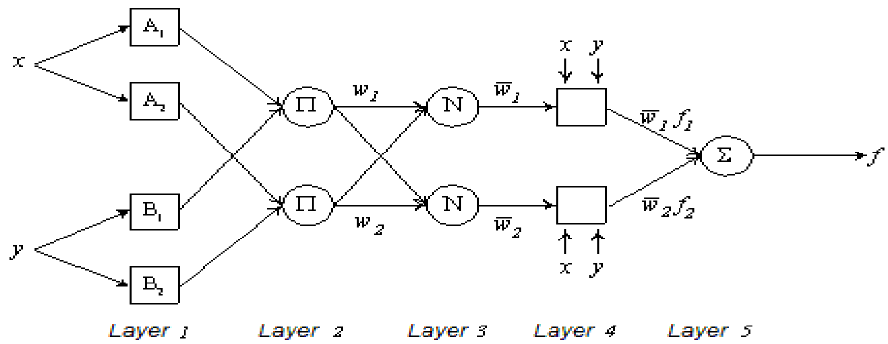

Fig.2. Architecture of ANFIS equivalent to a first-order sugeno fuzzy model.

The model has five layers where circular nodes represent nodes that are fixed whereas the parameters of square nodes have to be learnt. ANFIS learning rule is a combination of back-propagation and least-squares algorithm to determine and optimize the Sugeno system's parameters. Training the ANFIS is a two-pass process over a number of epochs. During each epoch, the node outputs will be calculated up to layer 4. At layer 5, the consequent parameters will be obtained using a least-squares regression method. The output of ANFIS is calculated and the errors will be propagated back through the layers in order to determine the premise parameter (layer 1) updates.

A two rule Sugeno ANFIS has rules of the form (2008) [9]:

$$\text{Rule } \mathbf{1}\text{: } \boldsymbol{if}\ x\ \boldsymbol{is}\ A_1\ \boldsymbol{and}\ y \text{ is } B_1 \text{ th}\boldsymbol{en}\ \boldsymbol{f_1} = p_1\boldsymbol{x} + q_1\boldsymbol{x} + r_1 \tag{5}$$

$$\text{Rule } \mathbf{2}\text{: } \boldsymbol{if}\ x\ \boldsymbol{is}\ A_2\ \boldsymbol{and}\ y \text{ is } B_2 \text{ th}\boldsymbol{en}\ \boldsymbol{f_2} = p_2\boldsymbol{x} + q_2\boldsymbol{x} + r_2 \tag{6}$$

Layer 1, consists of adaptive nodes that generate membership grades of linguistic labels based upon premise parameters, using any appropriate parameterized membership function such as the generalized bell function. The nodes in layer 2 are fixed nodes designated Π, which represent the firing strength of each rule. The outputs of layer 3 are the normalized firing strengths. Each node is a fixed rule labeled N. The adaptive nodes in layer 4 calculate the rule outputs based upon consequent parameters using the function (2012) [10]:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_1 x + q_1 x + r_1) \tag{7}$$

Where w_i is a normalized firing strength from layer 3, and (p_i, q_i, r_i) is the consequent parameter set of the node. The single node in layer 5, labeled Σ, calculates the overall ANFIS output from the sum of the node inputs(Sumithira et al., 2012):

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i \boldsymbol{f}_i}{\sum_i w_i} \tag{8}$$

2.2. Mathematical basis of MLP

Artificial neural networks are a branch of artificial intelligence (AI) science which placed in computational intelligence (CI). These networks have been inspired by the human nervous system and have the ability to learn, store and recall information of the trained data. This technique has an efficient performance in non-linear mapping to transfer input to output multidimensional space. Neural networks have wide applications in various fields such as pattern recognition, image recognition, estimation, prediction, clustering and etc. Moreover, this method is used for modeling complex natural phenomena and engineering problems in many cases where there is no understanding of the relationship between different parameters. Generally the neural networks are formed from small processing units, called neurons. Each neuron consist of five sections which are: input layer, the based and biases, summation function, transfer function and targets. Neuron components are placed in three layers; input layer, hidden layer and target layer. In fact hidden layer includes summation function, transfer function, weights and biases. *Fig. 3* A shows the structure of the ANN with one hidden layer and Fig. 3B displays components of a neuron and general activation functions as well as their related characteristics are illustrated in Fig. 3C. Various previous studies have shown that up to three hidden layer would be sufficient for achieving an acceptable model. If the network has more than one hidden layer, inputs of second hidden layer are outputs of previous one. The most widely used activation functions in multi-layer perceptron (MLP) artificial neural networks are sigmoid and linear functions. MLP neural networks are commonly used in estimation and prediction of unknown data.

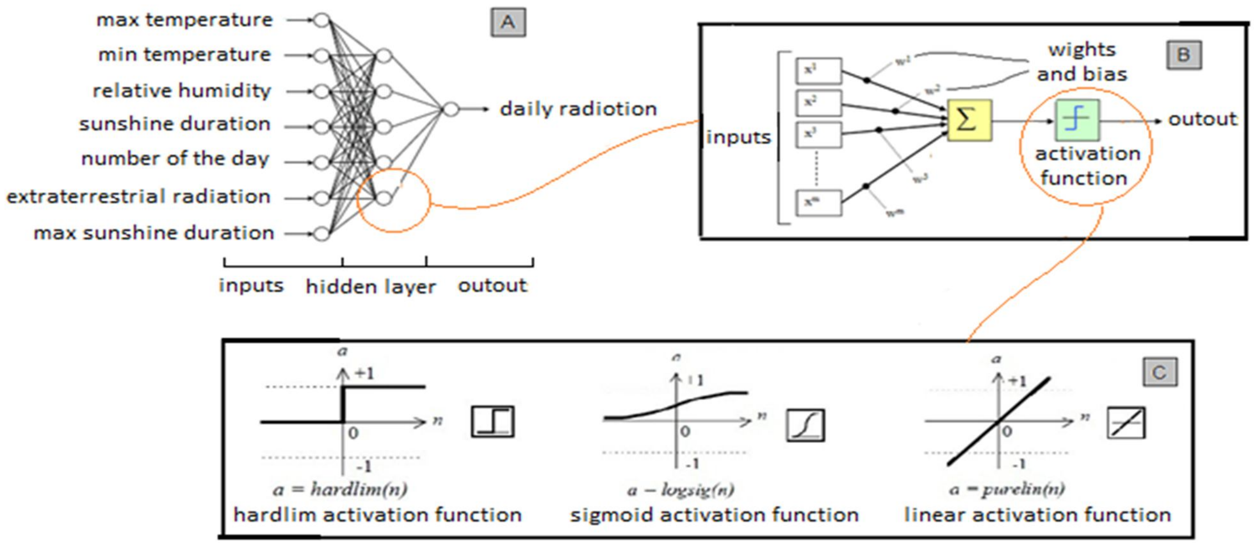

Fig.3. Components of an artificial neural network.

In ANNs, appropriate models are reached by using different algorithms which adjust and update weights in neurons, calls training neural network. There are two kinds of training neural network; supervised (Both inputs and target have specified for network) and unsupervised (network has no target data). Multi-layer perceptron neural networks use back-propagation (BP) algorithm. BP algorithm is a supervised training. In this training process, inputs data are applied to the ANN and network's output calculate by initial weights (They are randomly selected). Then, network's output is compared with the target and weight correction process is performed in the opposite direction of the gradient of the mean square error. So the difference between the network output and the desired output is reduced. Generally, modeling process by ANN consist of four steps, 1) collecting and preparation of data, 2) designing ANN components, 3) training the network, 4) creating the model by the weights and biases obtained from the training phase to respond to other inputs. Artificial neural network is proper to establish relationship between inputs and targets and compared to other modeling methods such as regression techniques, is considered as a fast and efficient way of modeling complex systems. In this study, the multi-layer perceptron neural network with two hidden layer is used. Respectively, sigmoid and linear activation functions are utilized in first and second layers and the network trains by Levenberg-Marquardt algorithm.

3. RESULTS AND CONCLUSIONS

Driving the collector's performance characterization from the conventional test methods which rely to the related standards needs costly test facilities and there are so many limitations in order to meet the standard's conditions. To overcome this problem, MLP and ANFIS methods are used for performance prediction of flat-plate solar collectors. These models are trained and tested with different network structures.

As shown in *table 1* both methods are capable to predict flat-plate solar collectors' performance with minimum acceptable root mean square error (RMSE), maximum correlation coefficient (R^2) and low mean bias error (MBE). The best results in applied methods belong to the third ANFIS with R^2= 99.5 %, RMSE=0.047 and MBE=0.0001. Among MLP models (*table 1*) the third one with (14, 7, 1) neurons respectively, in network layers structure has the best result with R^2= 0.994, RMSE=0.048 and MBE=0.0008.

Table1. ANFIS and MLP models for predicting flat-plate solar collectors' performance.

Table1. ANFIS and MLP	**ANFIS**				**MLP**			
	Number of Clusters	**R^2**	**RMSE**	**MBE**	**Network Structure**	**R^2**	**RMSE**	**MBE**
1	30	0.993	0.050	0.0002	12-6-1	0.986	0.090	0.0083
2	67	0.932	0.175	0.0001	12-8-1	0.929	0.163	0.0003
3	62	0.995	0.047	0.0001	14-7-1	0.994	0.048	0.0008
4	54	0.992	0.052	0.0007	12-7-1	0.993	0.058	0.0001

As it is represented in *Fig. 4*, artificial intelligence techniques (MLP and ANFIS) are powerful tools for performance prediction of flat-plate solar collectors with satisfactory accuracy particularly ANFIS models give better prediction with lower root mean square error. *Fig. 4-a* and *4-b* represent the MLP prediction and *Fig. 4-c* and *4-d* are belong to ANFIS prediction of flat-plate solar collectors' efficiency. It can therefore be concluded that investigated methods in this study are able to predict the collectors' performance with suitable precision and have acceptable potential to replace with conventional collectors' test methods which are costly and time consuming.

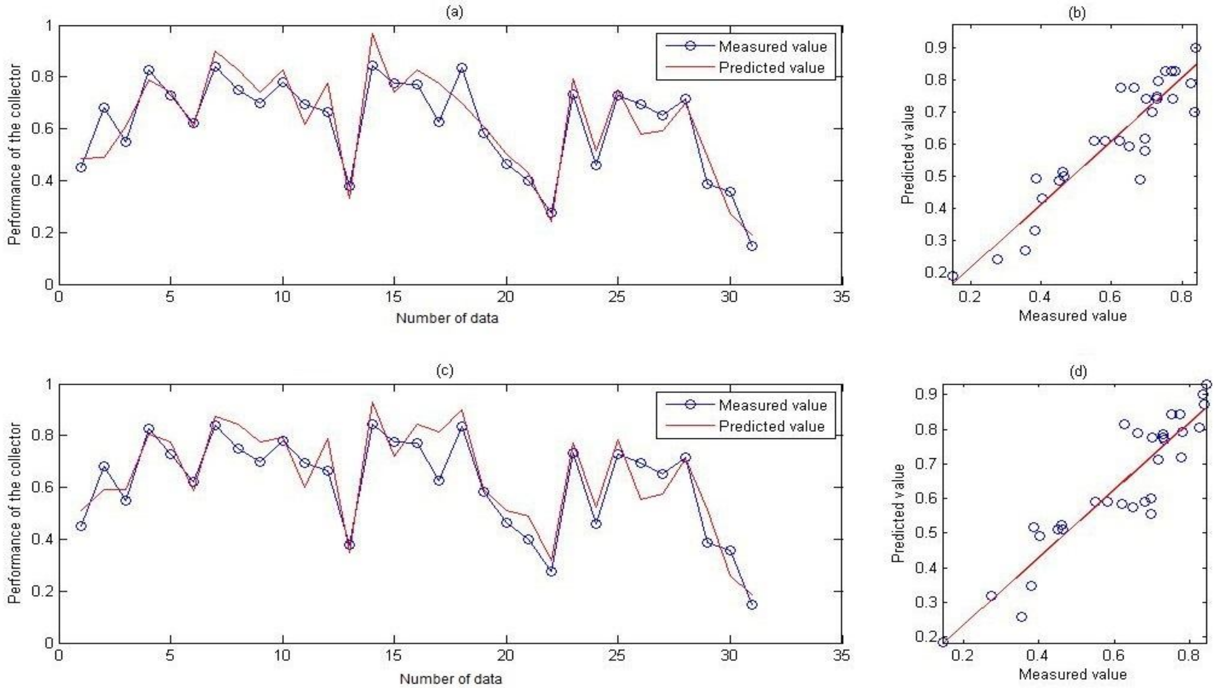

Fig.4. Comparison between measured and predicted results.

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