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Generating hot water by solar energy and application of neural network

Cuma Cetiner, Fethi Halici, Hamit Cacur, Imdat Taymaz *

Department of Mechanical Engineering, Sakarya University, Esentepe Campus, 54187 Adapazari, Turkey

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Abstract

Solar technology already boasts a century of research and development, requires no toxic fuel and relatively little maintenance, is inexhaustible and with adequate financial support, is capable of becoming directly competitive with conventional technologies in many fields. These attributes make solar energy one of the most promising sources for many current and future energy needs.

In this study, an experimental solar hot water generator, consisting of a cylindrical concentrator, an absorber, a heat exchanger, a water store, a pump and a control unit has been constructed and tested in order to establish the thermodynamic efficiency of the system.

Experimental data were obtained and used to train an artificial neural network in order to implement a mapping between easily measurable features such as environmental conditions, input and output water temperatures, solar radiation and flow rate of hot water.

Keywords: Hot water generation; Solar energy; Neural-network

* Corresponding author. Tel: +90 264 346 0353; fax: +90 264 346 0351.
E-mail address: taymaz@sakarya.edu.tr (I. Taymaz).

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Nomenclature

a	real value
A_c	surface area of the reflecting mirror (m^2)
A_r	absorber surface area (m^2)
C	concentration ratio
c_p	constant pressure specific heat of the water (kJ/kg K)
I_{dr}	direct radiation (W/m^2)
$\dot{m}$	mass flow rate (kg/s)
ME	mean square error
MRE	mean relative error
p	predicted value
$T_{r\text{-}in}$	inlet temperature of water (°C)
$T_{r\text{-}out}$	outlet temperature of water (°C)
ηd	thermal efficiency of the system

1. Introduction

After the energy crises of the 1970s and the subsequent increases in the cost of petroleum-based fuels, interest in active solar energy systems surged. Increasing of energy needs and decreasing of the fossil based energy sources, accelerates the researches for the alternative energy resources. Thousands of systems were installed from the late 1970s through middle 1980s. Alternative energy resources are far less polluting than traditional fuels, although they may have other drawbacks. The great feature of solar energy is the fact that it is likely to continue to exist so far into the future that we can think of it as being unending. Sunlight can be concentrated by solar collectors. For many applications it is desirable to deliver energy at temperatures higher than those possible with flat-plate collectors. Energy delivery temperatures can be increased by decreasing the area from which heat losses occur. Many designs have been set forth for concentrating collectors.

Studies about concentrating collectors sped up in early 1970s by the oil crisis. Thomas and Güven investigated the thermal analysis of the cylindrical and parabolic concentrator and optic errors related to manufacturing [1]. Halici has evaluated the performance of the concentrating collectors having a constant absorber [2]. Odeh and coworkers have produced steam by using synthetic oil as a working fluid in a parabolic type reflector in 1997. The produced steam was used to work a Rankine turbine and its efficiency and thermal loss were calculated [3]. Kalogirou, in his experimental study, has produced steam in a low temperature with a parabolic focuser and worked on the system design and performance characteristics [4]. In these studies the parabolic reflector and absorber in the focus are tracing the sun light in together. In the present study, focus surface is kept fixed, and the cylindrical reflector traces the solar rays.

Solar thermal systems convert sunlight into heat. Flat-plate solar thermal collectors produce heat at relatively low temperatures (27–60 °C), and are generally used to heat air or a liquid for space and water heating or drying agricultural products. Concentrated collectors achieve higher temperatures by using a concentrating reflector to direct sunlight from a large area to a smaller receiver and absorber area. A liquid is pumped through the absorber, where it is heated and then sent to a storage system or used directly for heating. Concentrating collectors work best in climates that have a high amount of direct solar radiation. They do not function as well on cloudy days, when available solar radiation is mostly diffuse. The available, the size of the reflector, how well they concentrate solar energy on to the receiver, the characteristics of absorber, and the control of the flow rate of the heat transfer fluid.

A concentrating collector system can have a fixed or stationary collector, or it can track the sun. In stationary systems the reflector and absorber are in a fixed position, usually oriented directly true south. Tracking devices shift the position of the reflector and the receiver to maximize the amount of sunlight concentrated on the receiver. Tracking collectors are either single-axis or double-axis. The entire collector, containing the reflector and receiver, generally moves as a unit in both types. Systems with dual-axis tracking concentrate solar energy the most and therefore produce the highest temperatures, but are the most complex and expensive.

The purpose of using ANN is making use of data we have to predict the results of other data. Additional working hours and costs are not beaded at ANN. At this topic, there is limited number of studies. Using his experimental study, Kalogirou generated steam at parabolic collector and by using ANN he made system design and modeling, and he predicted regional concentration ratio and intercept factor. And he studied on performance prediction and modeling of water heating systems with solar energy [5].

In this experimental study, applicability and restrictions were researched by ANN modeling and a study for producing very hot water from solar energy. Finally, for different network entrances flow rates and efficiency changes are investigated.

2. Experimental setup

The experiments are performed in Denizli region, Turkey. The specifications of the experimental setup are shown in Table 1. The experimental set is based on 8 float mirrors placed on 2 different axes. Total area of the mirrors is 54 m^2. The mirrors located in two rows, can trace the sun automatically. The distance of the cylindrical surfaced mirrors to the focus point is 12 m. As seen in Figs. 1 and 2 the cross-sectional view of the reflector is nearly straight. The reason for this situation is because of the rate of the focus distance to the linear semi space is relatively large. This

Table 1
Experimental setup specifications

Item	Value/type
Number of collectors	2×4
Dimensions of collectors	3.20 m × 2.11 m each
Total area of collectors	54 m^2
Focal length	12 m
System lay out direction	North–south
Type of system	Polar
Mode of tracking	East–west

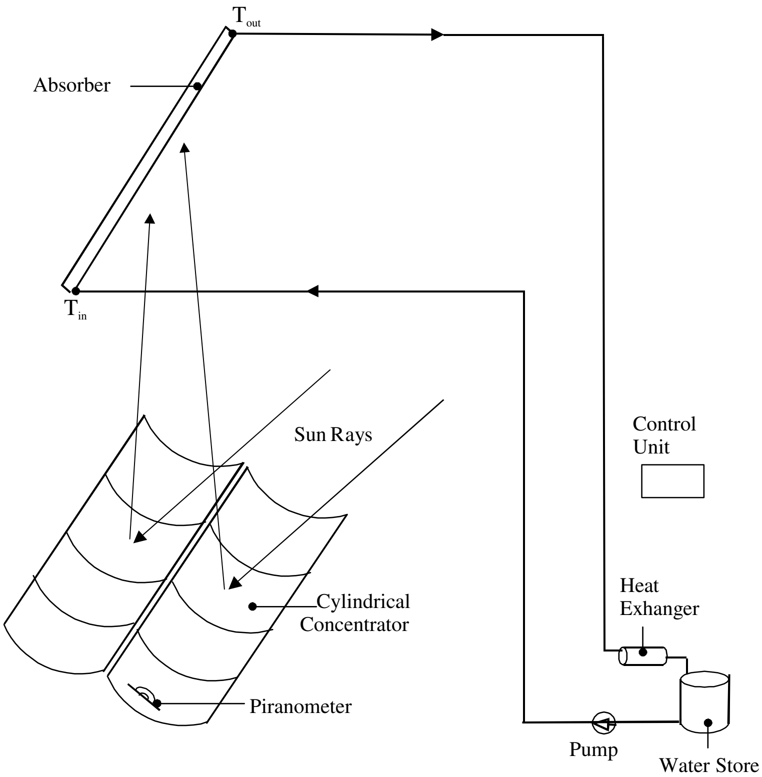

Fig. 1. Experimental set of fixed focused cylindrical concentrator.

also indicates that our experimental set is paraxial. Cylindrical surface is accepted as a parabolic surface inside the paraxial area.

To locate the mirrors in the system, 8 float box made from cylindrical steel profile was constructed with the dimensions 2.3 m width and 3.4 m length. System is located from north to south direction and tracing the sun with one axis in the west–east direction. The system is placed horizontally with latitude angle (37.5°) of this region, so this is the polar system. The picture of the experimental set is given in Fig. 2. In the system, the reflector mirrors are tracing the sun and in the other side absorber ones are stay fixed.

The absorber is designed as a floating structure, which consists of five steel boxes containing 20 pieces of steel tubes with 8 mm diameter. Because of the fluctuation of the angles of the solar rays with seasons changing, the length of the absorber had to be lengthened 0.5 m on both ends and it became 14 m long.

To avoid the oxidation of the tubes inside the emitter, softened water with low oxidation property is used. The water is delivered again to the absorber by a pump after the heat of the very hot water recovered in the heat exchanger.

During the experiment, the solar radiation has been measured by a Kippzonen type pyranometer. The pyranometer is located on the mirrors. Total radiation and the amount of intellect solar radiation is measured in every 15 min. The wind velocity, surrounding temperature, water inlet

Fig. 2. Picture of the experimental set.

temperature to the absorber, and the temperature of the stored water are measured simultaneously with solar radiation. The amount of the very hot water is measured by weighing. The pressure of the very hot water is measured with a manometer.

3. Artificial neural networks (ANN)

Artificial neural networks (ANNs) mimic somewhat the learning process of a human brain. Instead of complex rules and mathematical routines, ANNs are able to learn the key information patterns within a multi-dimensional information domain. In addition, inherently noisy data do not seem to present a problem, because neural networks are tolerant to noise variations. One of the early applications of ANNs, that worked successfully for more than 25 years, dealt with adaptive filtering for noise reduction developed by Widrow [5,6]. It is widely used in technical robot design, control mechanisms, telecommunication, weather forecasting, medicine industry, manufacturing and planning, material sciences and power systems. ANN is also used in modeling the energy systems in recent years.

Artificial neural networks differ from traditional simulation approaches in that they are trained to learn solutions rather than being programmed to model a specific problem in the normal way. A neural network consists of a number of processing elements (neurons), each of which have many inputs but only one output. In a typical network there are three layers of neurons, i.e., input layer, which receives input from the outside world, hidden layer or layers which receive inputs from the input layer neurons and the output layer which receives inputs from the hidden layers and passes its output to the outside world and in some cases back to the preceding layers. The strength of the network lies in the interconnections between the neurons, which is modified during training. The training is done by exposing the network to a specific data set of information and by applying a training algorithm to enable the network to produce the desired output [7].

The most popular learning algorithms are back-propagation and its variants. The back-propagation (BP) algorithm is one of the most powerful learning algorithms in neural-networks. The training of all patterns of a training data set is called an epoch. The training set has to be a representative collection of input–output examples. Back-propagation training is a gradient-descent algorithm. It tries to improve the performance of the neural-network by reducing the total error by changing weights along its gradient [5].

In this study, a program called "Back Propagation-BP" whose mathematical basis is defined in the literature [8–11] is used to build the algorithm. This algorithm can make a good recognize, classification and generalization, and also a good model to set good connection with input and output. Learning algorithm is an iterative allocation algorithm, it can minimize the average error between the real (actual) output and the output which is wanted to be predicted by taking the square of the average of errors. After the learning level most appropriate values are saved and then new output and input values are wanted. Until the square of the error between the real (actual) values introduced to the network and the predicted values obtained in the output of the network, is minimized, the iteration can be continued by changing the weights between the neurons.

The data obtained from experiments (in Denizli region), the ambient temperature, ambient wind speed, the inlet temperature and the radiation on the mirrors, are the input values. The output value is the mass flow rate. A sigmoid function is used as transfer function. Because of the property of this function all the input data is normalized between 0 and 1 by using the equation:

$$N' = (N - N_{\min})/(N_{\max} - N_{\min}) \tag{1}$$

where $N_{\max}$ and $N_{\min}$ respectively, indicate the largest and smallest value of N, and N' the unified value of corresponding N. In selecting the optimum network parameters (learning rate, momentum coefficient, neuron number in hidden layer and iteration number) the program looks for the conditions where

$$\mathrm{ME} = \frac{1}{n} \cdot \sum_{i=1}^{n} |a_i - p_i| \tag{2}$$

Mean square error is minimum. Here, "n" is the number of the data, "a" is actual (desired) value, "p" is the predicted value. To evaluate the network performance "mean relative error" is calculated can be expressed as

$$\mathrm{MRE} = \frac{1}{n} \cdot \sum_{i=1}^{n} \frac{|a_i - p_i| \times 100}{a_i} \tag{3}$$

The experimental data, collected from the 32 experimental measurements, have been used to train a number of artificial neural-networks. From a total of 32 experimental measurements, 6 were randomly selected to be used as test patterns and the remaining 26 were used for training the network. To determine the optimum network parameters, the learning rate and momentum values are tested between 0.1 and 0.9, the neuron number in the hidden layer is tested between 2 and 7 and relative mean error is calculated for each of them. After many trials optimum network parameters are found; the learning rate is 0.75 and momentum rate is 0.85 and the neuron number at hidden layer is 7.

4. Experimental study

The experiment has started on September 10th of 2002 at 09:00 and ended the same day at 17:00. At the experiment, to measure the temperature, solar radiation, pressure and speed of wind, sensitive thermometer, pyranometer, manometer and ananometer is used consequently. The mass flow is measured by weight and in 15 min periods together with the other measurements. The value of the flow rate is calculated as a quantity by making measurements in 15 min periods.

Concentration ratios the one of the most important parameters in the collectors which is concentrating the solar radiation. Concentration ratio is the rate of the space area to the area of the absorber surface.

$$C = \frac{A_{\mathrm{c}}}{A_{\mathrm{r}}} \tag{4}$$

At the above relation, C stands for the concentration ratio, A_{r} for the absorber surface area (m^2), and A_{c} for the surface area (m^2) of the reflecting mirror [12].

The amount of heat transferred to the water at the absorber surface is calculated by the equation

$$Q_{\mathrm{s}} = \dot{m} C_p (T_{\mathrm{r\text{-}in}} - T_{\mathrm{r\text{-}out}}) \tag{5}$$

At the flat-plate collectors global radiation is used, however at the concentrated collectors direct radiation is used. For this calculation, the amount of the solar radiation coming to the mirror surface is calculated by using the values from the monthly average measurements of Meteorology of the Denizli region.

Thermal efficiency according to the direct radiation is the ratio of the amount of the heat transferred to the water with the direct solar radiation coming to the reflector surface

$$\eta_{\mathrm{d}} = \frac{Q_{\mathrm{s}}}{I_{\mathrm{dr}} A_{\mathrm{c}}} \tag{6}$$

is calculated.

At the beginning the direct solar radiation value coming through the mirrors is 475 W/m^2 but in the noon times it reaches to its maximum value of 902 W/m^2 as shown in Fig. 3. This value decreases in the evening at 17:00 to the value 590 W/m^2. The very hot water is weighted as the collected water amount after leaving the heat exchanger for 15 min. The amount of the very hot water is 80 l/h and maximum value is 270 l/h. And again the amount of the ambient temperature is 23.5 °C and then it was observed that it increases to the value 32 °C.

The wind velocity must be taken into account since it is one of the major loss sources of the absorber radiation. During the experiment, the wind velocity of the ambient during the day is

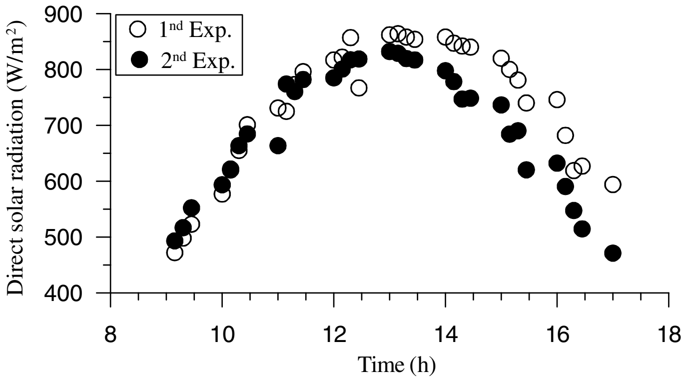

Fig. 3. Experimental set with direct solar radiation and efficiency graph of values obtained by ANN.

changing in between the values 2 and 5.5 m/sn. The very hot water is collected inside a storage as to resend it to the system. Because of the re-sending the same water from this storage to the system, at the beginning the temperature is 24 °C, then it increases to 50 °C at the end of the experiment.

Another experiment is established on May 10th of 1999 in Ankara [3]. In this experiment set, focal distance has 6 and 2 m aperture length. Ambient temperature varies between 14 and 24 °C. The flow out temperature of the water from the absorber is minimum 30 °C and it increases to 68.5 °C at the end of the experiment. As seen on Fig. 3, at the experiment direct radiation is 381 W/m^2 at 09:00. It increases to 819 W/m^2 at 13:00, and decreases to 386 W/m^2 at 17:00.

5. Application of the artificial neural-network

In the experiment ambient temperature, wind velocity, temperature to the entrance to absorber, amount of received radiation and obtained flow rate of hot water are calculated consequently. If we use these data with ANN, what will be the flow rate we can obtain in an experiment in different date and environment. From 32 experiment data, 26 data is given to the learning set, and randomly selected 6 data is given to the test set. In order to determine optimum network parameters, learning ratios and momentum coefficients between 0.1 and 0.9 are tried for every value between 2 and 7 of neurons at the hidden layer.

For the experimental data like inlet temperature to input layer, ambient temperature, inlet temperature into the absorber, wind velocity and direct radiation, 4 is entered. For the hidden layer where the weights affecting the calculations are processed, 7 is entered as a consequence of trial and error. As output value, for the flow rate and useful heat quantity, 2 is entered. After a few trials learning rate is taken 0.80 and momentum rate is taken 0.85 and calculations are done with these values. At the learning set, the error iteration was high at the beginning and because of that iteration process was repeated until minimum error was reached. Iteration process was completed at 10,000. At the learning set, mean relative error was 0.0016 at the beginning. After the iteration process was repeated for several times, this error has decreased suddenly, and it has become stable after 8000. The mean relative error takes the value 0.02% after the iteration process. This shows

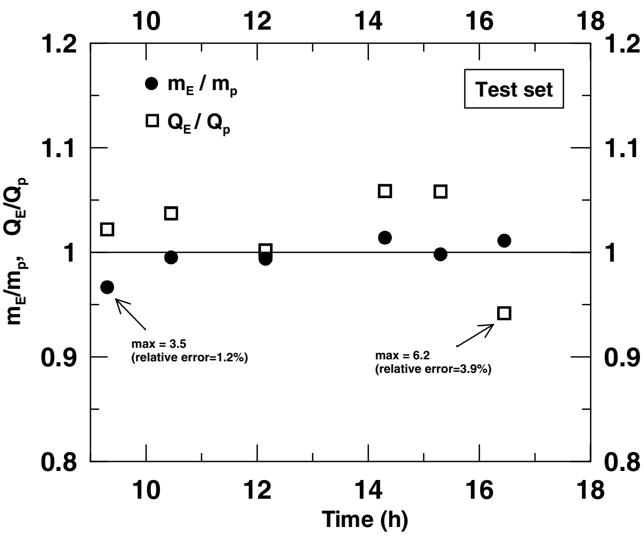

Fig. 4. Error ratios of values measured and predicted from test data.

that, the tested values are learned to be enough by the program and the error is in the acceptable level. Furthermore, the iteratively given 6 test values, tested and predicted values are over one line as in Fig. 4. For mass flow, maximum error ratio is 3.6% and mean relative error ratio is 1.2%. Maximum error ratio for the heat transferred to the water is 6.2% and mean relative error ratio is 3.9%. Mean relative ratio for experimental data at ANN program learning set is 7.1% and maximum error ratio is maximum 0.87%. For the rate of heat transfer, mean relative error is 9.1% and maximum error ratio is 1.1%. Afterwards, data from another experiment which has different

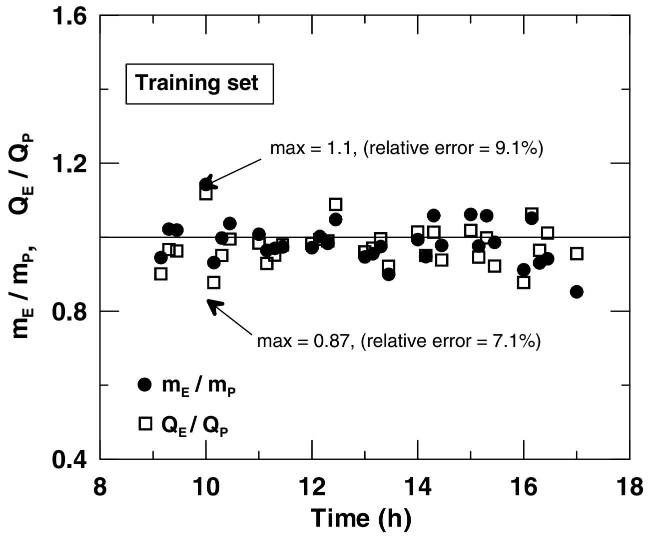

Fig. 5. Error ratios of experimental and predicted data at the learning set.

ambient temperature and direct solar radiation values, are given to the system for testing and results according to these data are obtained. These data belonging to the second experiment are given to the program for prediction of the flow rate and heat quantity. As shown in Figs. 4 and 5, ANN can predict the flow rate ratio and heat quantity to transferred to the water with small error differences.

6. Results

Fig. 6 represents the variation of the system efficiency with the time. In this figure, the system reaches to the maximum efficiency of 40% according to the direct radiation. This efficiency decreased to the value 15% in the morning and evening hours. The most obvious negative factors over the efficiency are the overshadowing of two mirrors to each other, the overshadowing of the concentrator to the system in the noon hours and overshadowing of the construction over the mirror. Beside these, cloudy and windy weather is negatively effecting to the efficiency in this open environment experiment, even though the experiment was done in an open-windly weather. The wind velocity do not reach to the value of 5.5 m/s most of time. Some heat losses were observed with convection in the concentrator because of wind. In Fig. 8, power supplied by the system was 18 kW maximum at noon and 6 kW minimum in the afternoon.

In this study, following the identification of system characteristics using the principles of ANN, the outputs for a predetermined test input are predicted. The wind velocity and inlet temperatures are kept constant, but amount of convection and ambient temperature are changed in these data. The predicted values for different convection and ambient temperatures are obtained by searching the flow rate that can be obtained from the system and heat quantity. The obtained results are acceptable for engineering purposes. As shown in Figs. 7 and 8, mass flow rate and useful energy have values with a slope parallel to the slope of experimental data. In both graphics, predicted values are lower than the experimental data. Reasons for such deviations related with is that ambient temperature and solar radiation values of the second experiment are lower than these values of the first experiment. It is observed that our system works with a lower efficiency under these parameter conditions. Using higher ambient temperature and solar radiation values than experimental data for the system, higher predictions would be obtained.

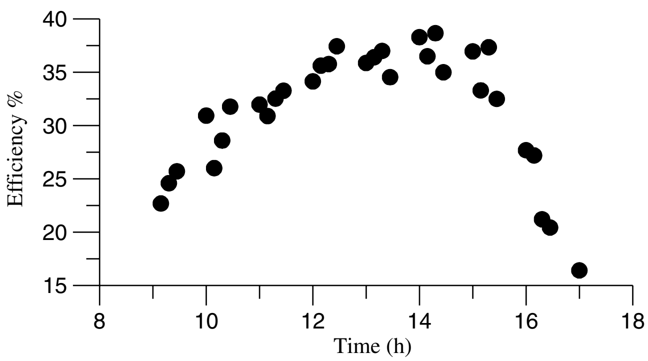

Fig. 6. Experimental set efficiency.

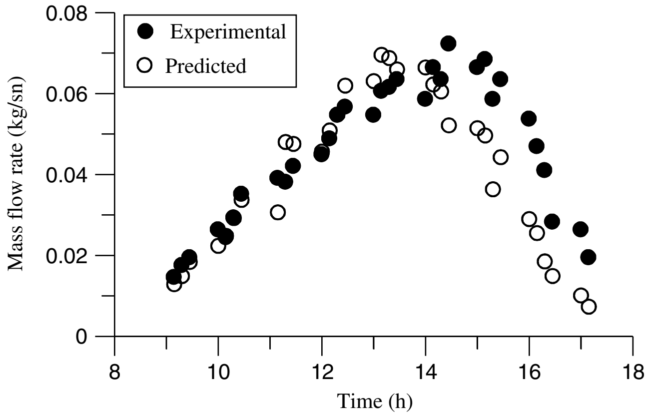

Fig. 7. Mass flow ratio obtained from the experiment done in first experiment (in Denizli region) and ANN predicted values for the second experiment (in Ankara region).

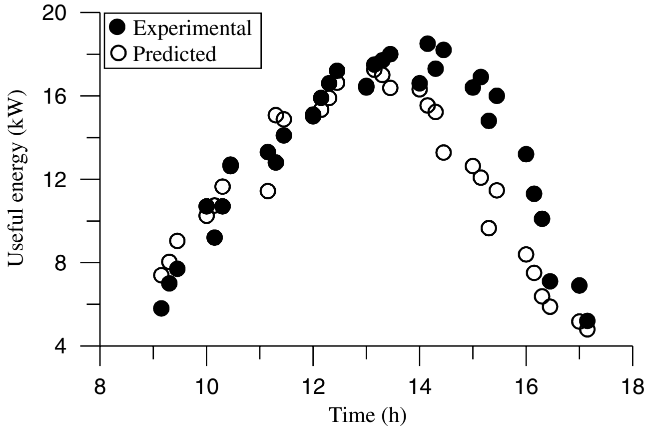

Fig. 8. Variation of useful energy transferred to the water.

7. Conclusions

This experimental results presented in the paper show that the system has proved 40% efficiency from the use of solar radiation. In addition, power supplied by the system was 18 kW maximum at noon and 6 kW minimum in the afternoon.

The design of the neural network model includes the number of hidden layers, the hidden neurons, the activation function of the hidden layers, the learning rate, and the goal error along with the initial weights and biases. Neural-network-based models have simple structure and are not difficult to obtained based on measured input–output data. If we want to gain a network with high prediction accuracy, we need a large quantity of sample to train the network.

With ANN, by using a well trained network, useful energy, mass flow rate and other parameters can be obtained without doing additional experiments.

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