Modelling of biogas, solar and a ground source heat pump greenhouse heating system by using ensemble learning

H. Esen, M. Esen, and T. Yuksel

Abstract-In the present work, the biogas, solar and a ground source heat pump (BSGSHP) greenhouse heating system which will be modeled by ensemble model (neural network (NN), support vector machine (SVM) and K-nearest neighbors (K-NN)) has eight inputs and one output. Due to high heating costs and fossil fuel use, the interest in alternative or renewable energy sources for greenhouse heating is currently high. When we compare NN results with the results that are obtained with ensemble model, we can see easily the superiority of the ensemble model.

Keywords- Biogas, ensemble learning, ground, neural network.

I. Introduction

Greenhouse is a structure that growing plants. These structures are used in the industry, from small to large structure construction. Greenhouses allow for greater control over the growing environment of plants. Due to population growth, the need is met greenhouse for agricultural products. Hence, the demand for greenhouse food industry is increasing over the years [1-3].

A solar greenhouse collects and stores heat during the day, keeps the heat inside at night and on cloudy days. A solar greenhouse is oriented to maximize southern glazing exposure [4].

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Greenhouse industry, a growing issue in agriculture in Turkey, chiefly because of favorable climatic conditions. However, for the healthy growth of plants, plants still need to heat during the winter night. Greenhouse heating is among the most energy-consuming activities during the winter season in our country.

In many energy systems applications, performance/ efficiency prediction is very important. It is recommended that intelligent systems (artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), support vector machine (SVM) and ensemble model) can be used to estimate the performances/efficiencies of thermal systems in engineering applications. More specifically, they used ANN for quasi-steady-state modelling of the greenhouse environment [5-6], for model dynamics [7] for reminiscent model-based optimization and for constructing an expert decision system. Seginer [8] illustrated some ANN applications to greenhouse environmental temperature control. Two examples are the mimicking of a model-based optimal (feed-forward) controller and a human optimizer (expert grower), who uses some feedback information from the state of the crop. Blasco et al., [9] have focuses on development of control algorithms by incorporating energy and water consumption to maintain climatic conditions in greenhouse. Ehret et al., [10] are developed and tested the concept of using neural network models to accurately predict cuticle cracking in both pepper and tomato fruit from growing conditions in commercial greenhouses. Speetjens et al., [11] have showed the suitability of the extended Kalman filter (EKF) for automatic, on-line estimation and adaptation of parameters in a physics-based greenhouse model. Wang et al., [12] presents the support vector machines regression modeling method and online learning approach for the greenhouse environment and is structured. Ma et al., [13] examined the greenhouse temperature model based on ANFIS, using the experimental data to adjust the parameters of the model and

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parameters can be determined ultimately converge to some value.

The purpose of this study was to show that a BSGSHP greenhouse heating system have been planned and placed into the greenhouse. In addition to, BSGSHP system which will be modeled by ensemble model has eight inputs and one output. In all cases, the ensemble model performed successful results.

II. BSGSHP SYSTEM DEFINITION AND EXPERIMENTAL VALIDATION

This study analysed the greenhouse structure has been established in a village 25 km west of Elazığ, Turkey. In the literature, it is stated that the greenhouse temperature be kept in the 23 °C [14]. The sizes of the sera used in this study are 4 m x 6 m x 2.1 m. The greenhouse was made of polycarbonate material. The used polycarbonate sheets are 6 mm twin-wall panels, and are almost as transparent as glass.

Experiments conducted with BSGSHP system under steady-state conditions in the heating mode 2009 and 2010 years. The temperature measurement points (red color) of experimental study are given in Fig. 1.

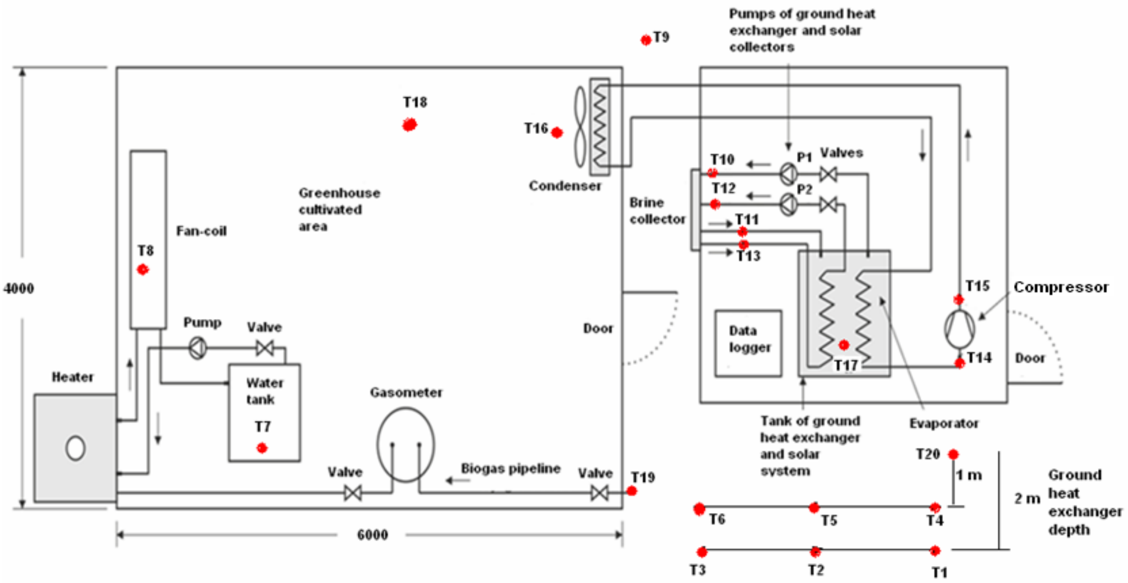

Fig. 1. The sketch of temperature measurement points of BSGSHP system

The temperatures (T1, T2, T3, T4, T5, T6: ground; T7: biogas water tank; T8: blowing up fan-coil; T9: outdoor area; T10: inlet of ground heat exchanger (GHE); T11: outlet of GHE; T12: inlet of solar collectors; T13: outlet of solar collectors; T14: inlet of compressor; T15: outlet of compressor; T16: condenser fan; T17: tank of GHE and solar system; T18: indoor greenhouse; T19: generator; T20: ground at 5 cm).

The heat rejection rate in the condenser is calculated by

$$\dot{Q}_{con} = \dot{m}_{ref}\,(h_{con,i} - h_{con,o})\,. \tag{1}$$

The heat transfer rate in the evaporator is

$$\dot{Q}_{eva} = \dot{m}_{ref}\,(h_{eva,o} - h_{eva,i})\,. \tag{2}$$

The work input rate to the compressor is

$$\dot{W}_{comp} = \frac{\dot{m}_{ref}\,(h_{comp,o} - h_{comp,i})}{\eta_{icomp}\eta_{mcomp}}\,. \tag{3}$$

Hence, the COP of the BSGSHP can be determined as

$$COP_{hp} = \frac{\dot{Q}_{con}}{\dot{W}_{comp}}\,. \tag{4}$$

The coefficient of performance of the entire system (COP_{sys}) is calculated by the following equation,

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$$COP_{sys} = \frac{\dot{Q}_{con}}{\dot{W}_{comp} + \dot{W}_{pumps} + \dot{W}_{fancoil}}. \tag{5}$$

In the first part of the experiment, soil temperatures were utilized without an external heater. In the last part of the experiment, the generator was prepared. Mesophilic fermentation were kept for 45 days at a temperature between 25 °C and 38 °C. According to information obtained from the literature survey, generator temperature is kept at a constant 27 ± 3 °C. The released amount of biogas for the duration of experiments under these conditions is given in Fig. 2. During this experiment, the amount of biogas produced from the generator is about 2200 liters.

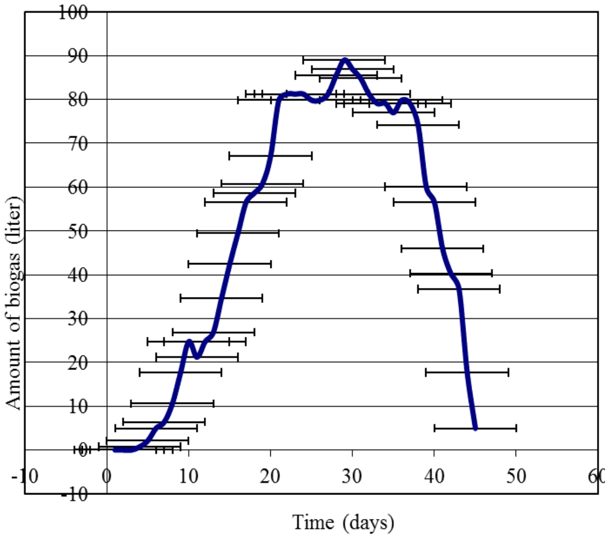

Fig. 2. The amount of produced biogas

In this period, the exchange according to the days of the amount of gas produced by the soil, reactor and outdoor air temperatures are shown in Fig. 3. A maximum amount of gas produced in the 29 day period was 89 litres.

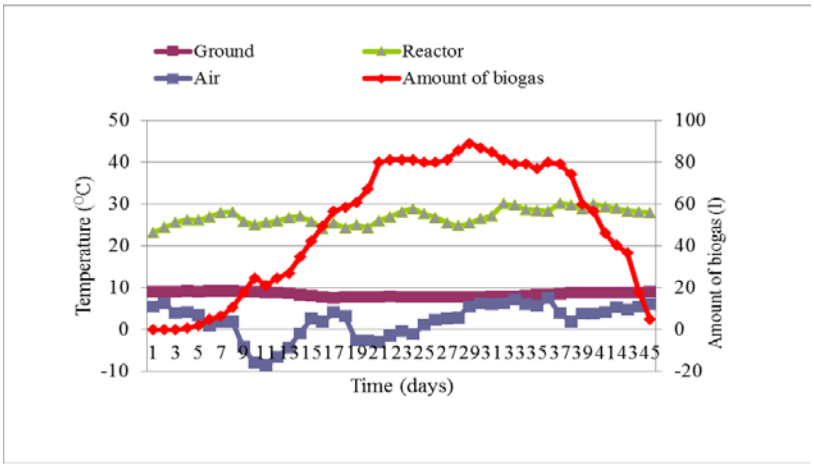

Fig. 3. The exchange according to the days of the amount of gas produced by the soil, reactor and outdoor air temperatures

Main heat loss from greenhouse occurs at night. Heat loss between 7 am and 8 pm is 5 kW. Average daily heat loss is 4.67 kW. The gas produced from generator under mesophilic conditions was measured by gasometer. The gas exiting gasometer is then reached the water heater. The gas obtained from the gasometer pressurizing prepared for combustion in the water heater. The hot water enters to the fan-coil where it carries its heat to the greenhouse, and then distributed through the water tank another time. This progression is repeated to increase the temperature of water in the tank. When the water temperature reaches approximately 45 °C, the system automatically stops for preventing fuel consumption. The greenhouse air, outside air, tank water, and fan-coil air temperatures measured for biogas system are shown in Fig. 4.

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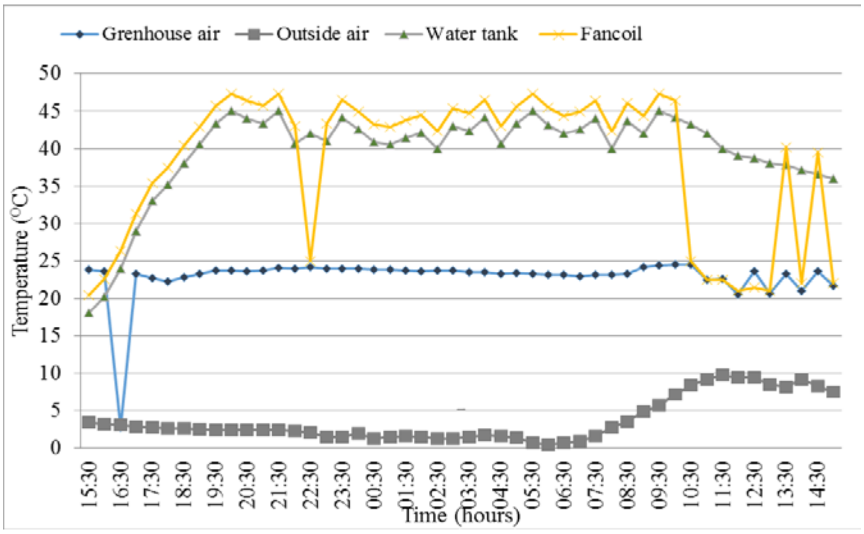

Fig. 4. Temperature change of greenhouse environment, outside air, tank water and fan temperatures

When the greenhouse internal temperature reaches 23 °C (according to ref. [14] greenhouse temperature range is set between 20 °C and 29 °C), the fan-coil unit stops. Hence, the greenhouse temperature does not increase and power consumption reduces.

Ground heat exchanger (GHE) in the established system is slinky (spiral). To prevent freezing of water during the winter, antifreeze is added to the water. The water-antifreeze solution in the slinky GHE (see Fig. 1) extracts heat from the earth and carries it into the tank of GHE and solar system. The solution transfers its heat to refrigerant (Freon 22) fluid in the evaporator of the heat pump. The refrigerant evaporates by absorbing heat from the solution and then enters the compressor. The refrigerant is compressed by the compressor and then enters the condenser, where it condenses. A fan blows across the condenser to move the warmed air of the greenhouse. The GSHP system is disabled as the biogas system when the indoor air temperature reaches 23 °C. When the temperature drops below 20 °C, the GSHP system automatically stops. At night and in cloudy conditions, the GSHP system operates successfully alone. The average system performance is calculated as 2.48. According to the literature, this value is moderate [15-17].

III. Ensemble Learning

The ensemble learning is to employ multiple modeling methods and combine their results [18]. Ensemble approach is a mixture of various models (Neural Network (NN), Support Vector Machines (SVM) and decision tree) [19].

SVMs are supervised learning models which aim to achieve data analyzing, patterns recognition and classification and regression analysis based on a linear arrangement of structures derived from the variables [20] SVM uses nonlinear kernel functions to change the input data to a high dimensional feature space in which the input data becomes more manageable compared to the original input space. Moreover, in the classification problem, SVM aims to find a mathematical characterization of a hyper plane that separates the training data into several classes.

K-NN is one of the well-known classification methods [21-22]. It learns by comparing a given test tuple with training tuples that are similar to it. When a new instance is introduced, K-NN finds the k-nearest neighbors of this new instance and determines the label of the new instance by using these k instances. An example of k-NN classification is depicted in Fig. 5 [23]. The test sample (green circle) should be classified either to the first class of blue squares or to the second class of red triangles. If k = 3 (solid line circle) it is allocated to the second class because there are 2 triangles and only 1 square inside the inner circle. If k = 5 (dashed line circle) it is allocated to the first class (3 squares vs. 2 triangles inside the outer circle).

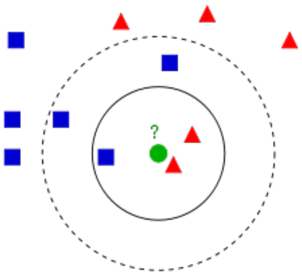

Fig. 5. An example of K-NN classification

In *k*-fold cross validation dataset is randomly split into *k* exclusive subsets of nearly equal size and the holdout method is repeated *k* times. At each time, one of the *k* subsets is used as the test set and the other *k-1* subsets are put together to form a training set. The advantage of this method is that it is not important how the data is divided. Every data point seems in a test set only once, and seems in a training set *k-1* times. Therefore, the verification of the efficiency of the suggested method against to the over-learning problem should be revealed.

To evaluate the results obtained models need to use some statistical approaches. Some statistical methods, such as the root-mean squared (RMS), the correlation coefficient (R), and the coefficient of variation (COV) may be used to compare predicted and actual values for model validation.

The error can be calculated by the RMS, defined as [24-25]:

$$RMS = \sqrt{\frac{\sum_{m=1}^{n} (y_{pre,m} - t_{pre,m})^2}{n}}, \tag{6}$$

In addition, the correlation coefficient (R), and the coefficient of variation (COV) in percent are defined as follows:

$$R = \frac{\sum_{m=1}^{n} ((y_{pre,m} - y_{mea})(t_{pre,m} - t_{mea}))}{\sqrt{\sum_{m=1}^{n} (y_{pre,m} - y_{mea})^2 \sum_{m=1}^{n} (t_{pre,m} - t_{mea})^2}} \tag{7}$$

$$COV = \frac{RMS}{|t_{mea}|} 100 \tag{8}$$

where n is the number of data patterns in the independent data set, y_{pre} indicates the predicted, t_{pre} indicates the actual dataset. t_{mea} and y_{mea} is the mean value of measured and predicted data points respectively.

IV. Simulation Results

In this study, BSGSHP greenhouse heating system which will be modelled by ensemble model has eight inputs and one output. Ground temperatures at 2 meters (Tg), brine solution entering temperature (Twa,i), brine solution leaving temperature (Twa,o), biogas tank temperature (Ttank), greenhouse temperature (Tgh), fan-coil temperature (Tfc), ambient temperature (Ta), the value of solar radiation (I) constitutes the input variables of the model. The COP_{sys} is the output variable of the ensemble model. The data set for the available system included 33 data patterns. Due to the 3-fold cross validation test 22 data patterns were used for training the ensemble model and the remaining 11 patterns were used as the test data set for trained ensemble model.

We used 13 neurons for hidden layers of the NN topology. We chose the linear activation function for the output layer. Moreover, the perceptron learning algorithm is used. For finding the optimum parameters for SVM, we investigated a search mechanism in the 2D gamma vs. sigma plane for obtaining the optimum gamma and sigma values [24, 26]. The Radial Basis Function (RBF) kernel is selected which yielded the best performance in the experiments. For K-NN, we set the k value as 3.

The prediction results of the ensemble modeling for BSGSHP system are presented in Table 1. The last raw of Table 1 shows the average prediction result of the 3-fold cross validation. In all cases, the ensemble model performed successful results. As the results indicate, Ensemble prediction method performed reasonably well in modeling the graduate scores.

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Table 1. Ensemble prediction result for BSGSHP

		RMS	Correlation coefficient (R)	COV
Ensemble model	First fold	0.0009	0.9995	0.0402
	Second fold	0.0027	0.9903	0.1073
	Third fold	0.0012	0.9921	0.0485
	Average	0.0016	0.9940	0.0653

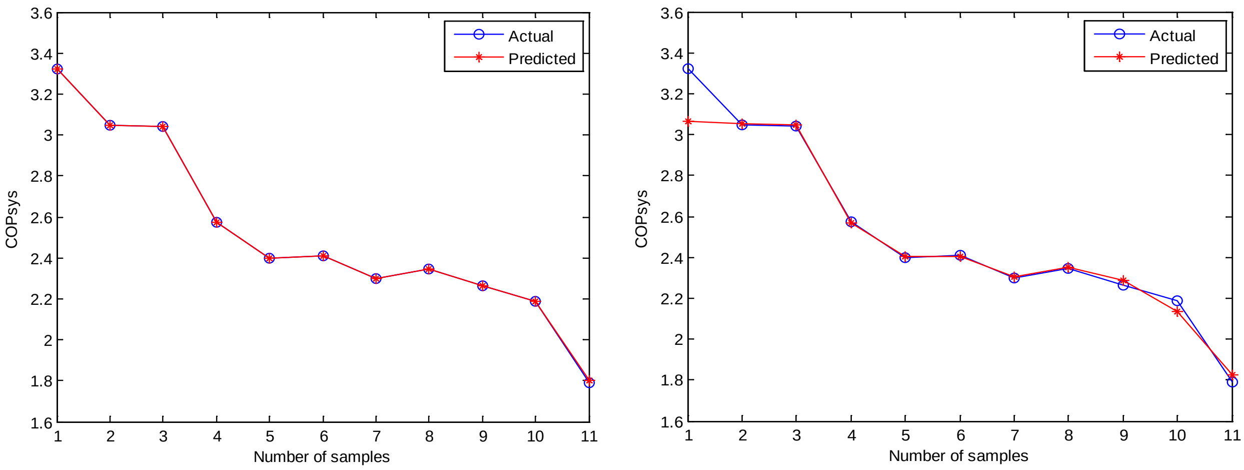
Average 0.0016 RMS, almost 100 % correlation coefficient (R) and 0.0653 COV values are obtained. Moreover, we compared the ensemble model with a single model. We selected the NN structure because of its wide usability property. In Table 2, the NN results are tabulated.

Table 2. NN prediction result for BSGSHP system

		RMS	Correlation coefficient (R)	COV
NN model	First fold	0.1974	0.9754	7.8331
	Second fold	0.0803	0.9868	3.2176
	Third fold	0.1189	0.9798	4.7892
	Average	0.1322	0.9807	5.2800

As we can see that NN modeling algorithm produced reasonably prediction results, where average 98.07 % correlation coefficient (R), 0.1322 RMS and 5.2800 COV values are obtained with 3-fold cross validation test. The worst results are obtained by the NN method for first fold of the database where lower correlation coefficient, and (97.54%) and higher RMS (0.1974) and COV (7.8331) values are recorded. When we compare NN results with the results that are obtained with Ensemble model, we can see easily the superiority of the Ensemble model.

Figure 6 shows the graphical illustration of the actual and predicted samples for Ensemble model and NN for second fold of the dataset. There are 11 test samples. As we can see that the Ensemble predictions are close enough to the actual samples.



(a) (b)

Fig. 6. Prediction results for first scenario (a) Ensemble method and (b) NN

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V. Results and Discussions

The results and recommendations from this study are listed below:

i) Using the heating process of biogas, energy saving is provided. Chemical reaction of methane in the generator, the temperature of the generator remains constant. Thanks to the biogas system, the greenhouse temperature remains at a constant 23 °C.

ii) Slinky types of GHE is proved to be successful in the greenhouse heating. During the experimental studies, we have seen that low (1 °C) soil temperature swings.

iii) High storage temperatures with solar energy systems can be obtained. Solar energy is stored in the soil and thus can support the biogas system.

iv) Ensemble prediction method performed reasonably well in modeling the graduate scores. Average 0.0016 RMS, almost 100 % correlation coefficient (R) and 0.0653 COV values are obtained.

v) Prediction of system performance values are compared with data obtained from an experimental study. Ensemble model with simulation studies, we found to be effective in energy applications.

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