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A novel enhanced exergy method in analyzing HVAC system using soft computing approaches: A case study on mushroom growing hall

Sina Faizollahzadeh Ardabili[a,*], Bahman Najafi[a], Hadi Ghaebi[b], Shahaboddin Shamshirband[c,e,**], Ali Mostafaeipour[d]

[a] Biosystem Engineering Department, University of Mohaghegh Ardabili, Ardabil, Iran
[b] Mechanic Engineering Department, University of Mohaghegh Ardabili, Ardabil, Iran
[c] Department for Management of Science and Technology Development, Ton Duc Thang University, Ho Chi Minh City, Vietnam
[d] Industrial Engineering Department, Yazd University, Yazd, Iran
[e] Faculty of Information Technology, Ton Duc Thang University, Ho Chi Minh City, Vietnam

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ABSTRACT

Energy crisis concentrates attentions in the field of building energy consumption through optimization of HVAC control systems. Studying the HVAC systems and optimizing them will help to save energy. Exergy is defined as a new energy function that can maximize accessible work by the second law of thermodynamics. The present study, discusses about HVAC system that is in operation for mushroom growing hall. The Exergy destruction is calculated for HVAC and the whole system and is linked to effective parameters as independent variables. Adaptive neuro fuzzy inference system (ANFIS) and multi layered perceptron (MLP) methods are used to model the studied system. Accordingly, after training by different number of neurons in the hidden layer for MLP network and by different types of membership function for ANFIS method, 10 numbers of neurons were selected as the best number of neurons for MLP network and Gaussian type of membership function for ANFIS method. The results indicate that MLP by consumption of 11.556 kj/s more energy compared to ANFIS, imposes 1.343×10^{-5} \$/s more cost and 2.687×10^{-4} m^3/s more consumption of natural gas. Therefore, applying ANFIS model prevents energy, time, cost losses and more GHG emission, so it can be the best and suitable model to adopt in real system.

1. Introduction

Industrial and agricultural production units such as greenhouses and poultry farms are the main consumers of HVAC (Heating, ventilating and air conditioning) systems. A typical HVAC system has indoor and outdoor air loops, condenser, chilled water and refrigerant loops [1,2]. In buildings that are using HVAC systems, about 40% of energy consumption is directed to HVAC systems [3,4]. Energy crisis has caused more attention in the field of building energy consumption through optimization of HVAC control systems [5]. Therefore studying on this issue and optimizing these systems will help to energy saving discussion, especially now that the energy crisis is considered as a serious restriction. There are several studies in the field of optimization of HVAC systems. Hussain et al. [6] used fuzzy controlling method with the aim of finding a method to moderate the energy consumption. Wang et al. [5] studied energy conservation performance of one passive school building and classroom thermal comfort enhancement. They concluded that the optimal control system is optimizing energy consumption. Nowadays one of the most significant challenges is the escalating of energy demands [7]. These challenges have led to optimizing and efficient use of energy. Exergy is a new energy function [8]. Exergy is the maximum accessible work that is defined by the second law of thermodynamics [9–11]. Energy systems are the main targets of exergy analysis. In fact, exergy analysis is offering suitable and more efficient method compared to energy analysis for the study of energy cycles [12]. Because it can determine the actual values of losses and their causes [13]. Exergy discusses the energy in both terms of quality and quantity [14]. Exergy Analysis calculates the destroyed exergy in different parts of the system that are created by entropy [14–16]. The total Exergy is equal to the sum of destroyed exergy of each part. This Exergy destruction is equal to the energy which for various reasons that have not been converted to useful work. There are many studies that used exergy in optimizing thermodynamic systems. Studying HVAC systems are also part of the thermodynamic systems.

* Correspondence to: Department of Biosystem Engineering, University of Mohaghegh Ardabili, Ardabil, Iran.
** Correspondence to: Ton Duc Thang University, Ho Chi Minh City, Vietnam.
E-mail addresses: Sina_fa1990@yahoo.com (S. Faizollahzadeh Ardabili), Shahaboddin.Shamshirband@tdt.edu.vn (S. Shamshirband).

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Nomenclature

A	area (m^2)
h	enthalpy (kj/kg)
U	heat transfer coefficient
$\dot{m}$	mass flow rate (kg/s)
T	temperature (K)
Q	thermal energy (kj)
$\dot{Q}$	thermal power (kW)
P	pressure (kpa)
$\dot{E}x$	exergy rate (kW)
ψ_{Ex}	exergy efficiency
ω	humidity ratio
ϖ	molar humidity ratio
C_p	specific heat capacity at constant pressure
C_v	specific heat capacity at constant volume
R	gas constant

Subscribes

D	destruction
in	input
out	output
0	dead state
a	air
w	water

Alimoradi [8] presented exergy analysis for forced convection heat transfer in a heat exchanger and investigated the effect of operational and geometrical parameters on the exergy efficiency. Andersen et al. [17] presented the continuous time modeling that the model parameters were estimated using a ML method for the heat dynamics of a building. The estimated parameters seemed reasonable compared to the expected values of the equivalent thermal components and it gives a good description of the heat dynamics of the nominated building. Chengqin et al. [18] discussed the principles of exergy analysis in HVAC system in an analytical review of similar studies. Du et al. [19] presented a control-perfect index method to evaluate control of HVAC systems to achieve an ideal operation. The basis of this concept was to minimize the exergy loss in HVAC system.

Satyavada et al. [20] illustrated a modular control-oriented modeling for HVAC performance benchmarking with the ability to effectively catch all interaction between HVAC equipment that the user can add and remove as many components as desired. This method lead to improvements in occupants' thermal comfort while at the same time consistently attaining energy savings. Satyavada et al. [21] compared baseline and optimal PI strategies based on PI-auto tuning strategy to ensure the occupant's comfort and reduced energy consumption of HVAC systems.

In recent years, soft computing methods were used in most fields of science [1,22]. Soft computing methods are able to predict the target model [23]. Neuro-fuzzy inference system (ANFIS), artificial neural networks and many other methods are different types of soft computing. These methods are widely used in the field of energy and exergy analyzing in different systems. Based on reports from numerous researches, ANN method is one of soft computing methods that have been studied in various energy systems [24–26]. Keçebaş et al. [27] developed ANN modeling to predict the exergy efficiency of a geothermal district heating system. They used correlation coefficient (*r*) and root mean square error (RMSE) as performance parameters. The results showed maximum correlation coefficient and minimum RMSE value. It was concluded that the prediction model had high precision in prediction process. Park et al. [28] developed an artificial neural networks model for predicting exergy by utilizing the networks' feasibility of information extraction and self-organization. The results indicated that the trained mapping was able to characterize the development trend of exergy at different groups of sample sites in different time periods and the developed models were possible to predict exergy at contemporaneous and subsequent sampling times. Strusnik and Avsec [25] studied a computation model for a thermo economic analysis using an artificial neural network (ANN). The developed model used energy and exergy methods to compute the results of the MFs. Taghavifar et al. [29] selected 10 input variables to analyze most important objective of output parameters. They applied ANN model with capability to predict responses with great confidence. The results were acceptable and indicated the accuracy of prediction process.

The present study is performed in an agro-industrial cultivation of mushrooms in Ardabil province of Iran that used HVAC systems. According to the obtained results of this production unit, the highest cost is related to cooling, heating of growth rooms and repairing the HVAC systems. Therefore, it was decided to do a study on cooling and heating exergy of one growing hall. This identifies the most vulnerable areas of exergy destruction and picks up the most effective step to increase energy efficiency. The modeling of exergy of studied system creates a comprehensive model and helps to prevent the confusion, system complexity and extent of the debates.

As mentioned previously, the main purpose of this study is to calculate exergy destruction using thermodynamic equations that are presented by researchers and to model the exergy destruction using ANN and ANFIS methods based on experimental data. Accordingly, this study has four steps. The first step introduces the studied system. Second step calculates the exergy destruction using presented thermodynamic equations. The third step develops the prediction models

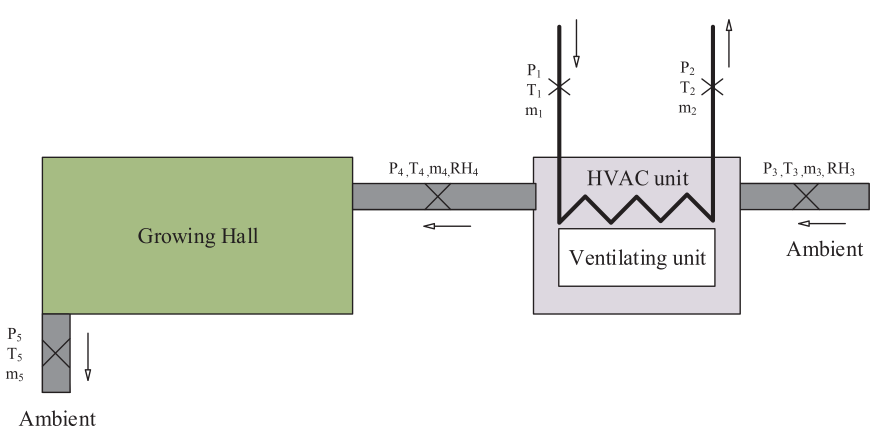

Fig. 1. A schematic of studied system.

based on related inputs and outputs and the last step presents the obtained results and compares the accuracy of the developed models and suggests the best and the most accurate prediction model.

2. Material and methods

2.1. Studied system

Ardabil Province is positioned in 38′ 15″ N and 48′ 17″ E and is one of the provinces of Iran. Experiments were carried out from a HVAC system in Sabalan Mushroom agro-industry, one of the broadest mushroom growing farms of Ardabil province. Fig. 1 illustrates an overview of general system.

The growing hall has an area of 143 m^2 and average height of 4.5 m. There are 5 parts that should be studied to calculate the system exergy and to indicate the exergy efficiency of the system. There are five PT-100 sensors, two HIH-4000 sensors and two manometers that were used in order to measure the temperature, relative humidity, and pressure of marked spots, respectively. All data were recorded via DAQ Master, the interface software of temperature measuring device, and a data logger for recording relative humidity data and also pressures were measured manually. By considering the season of experimental testing (winter), there was no need to cool circuit of system, therefore the study was performed on heating and ventilating sector of HVAC unit. Sabalan Mushroom agro-industry has 40 mushroom growing halls. In order to supply the required heating and cooling energies, there is a central boiling and a central chilling unit. Ardabil is located in a mountainous area of country and has the lowest annual average temperature (283.04 K) among other provinces of Iran [30]. Fig. 2 shows the average monthly temperature of Ardabil province from 2004 to 2014 according to the reports of Meteorological Organization of Iran [30].

According to Fig. 2, the highest temperature was accord on Aug (292.41 K) and the lowest temperature was accord on Jan (271.81 K).

The required temperature for growing the bottom mushroom is between 291.15 K and 297.15 K [31–33]. It is clear that the average temperature is more than 291.15 K, only on July and August, it means that the temperature for most months of the year is lower than the required temperature. Therefore, the need to heat the unit is more evident and accordingly the energy consumption in heating unit is allocated the highest amount. Optimization of energy consumption in this sector in a production plant can be an effective step in reducing costs and pollutions. The experimental testing was performed on February. Additionally, data recording process was performed on 20 working days of agro industrial farm. Then, the data of 16 days (80% of total data) were employed to model the system and the data of four days (20% of total data) were employed to validate the model. Fig. 3 indicates the average variation of daily temperatures in four days of week that were recorded by related sensor (Fig. 3).

In heating and air-conditioning systems of heat exchanger, liquid or gas flow is widely used. Heat transfer in a heat exchanger, which usually involves convection in each fluid and conduction through the wall separating the two fluids. Heat transfer between two fluids is a process that occurs on HVAC system [1]. The study of system was done based on some assumptions. By considering to that the experimental study on winter season, so there was no cooling process. Based on the calculations on experimental data, the efficiency factor of HVAC system in heat exchanging process was 0.78. The temperature of heating water during the day time is a constant value, because there is one central boiler for the entire collections of production room. So, the parameters that are able to change individually for one growing room are T_3, m_3 and m_1. The values of T_3 were obtained by data collector using the relevant sensor. The average daily temperature was extracted for a week on Jan 2015 (Table 1). Energy and exergy balances should be applied to each component to analyze the system [34] (Table 2).

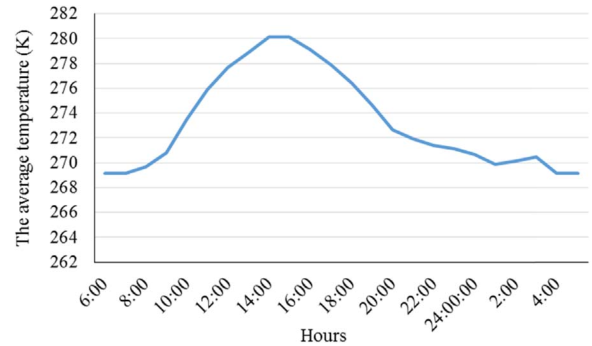

Fig. 3. Average daily temperature of four days.

2.2. Energy analysis

In order to evaluate the state of the system in terms of energy, the input, output and dissipated energies should be calculated. Therefore, the generated energy by HVAC should be calculated and be in balance with the energy losses and the required energy to keep the temperature constant condition that is one of the important factors of mushroom growing [31]. At first, the input thermal power of room that is generated by HVAC system ($\dot{Q}_{in}$) is calculated by Eq. (1):

$$\dot{Q}_{in} = \dot{m}_4 h \tag{1}$$

where h is the enthalpy of output air from HVAC system and m_4 is the output air flow from HVAC unit.

The second stage is to calculate the required thermal power for holding the growing hall temperature at a set point temperature (in this study the set point is considered 294.15 K, the average of 291.15 and 297.15 K). Therefore, the Heat Transfer (HT) from walls and roof using the heat transfer coefficients of the used construction materials should be calculated [31]. Then $\dot{Q}_{load}$ (thermal energy) is calculated by Eq. (2). It should be noted that time is not considered in calculating of thermal energy, but if the variation of temperature be assumed momentary (Fig. 3 and Tables 3 and 4), $\dot{Q}_{load}$ can be considered as thermal power for calculations:

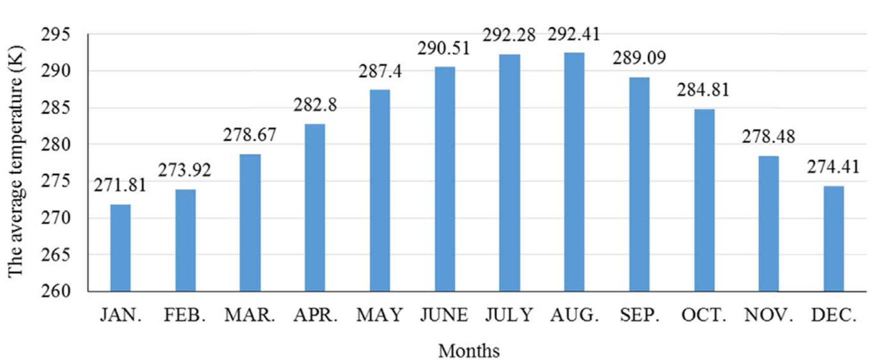

Fig. 2. Average monthly temperature of Ardabil province from 2004 to 2014.

Table 1
The results of recorded Data.

	Mean	Std. deviation	Std. error mean	Min	Max
T_{amb} (K)	285.35	12.44625	1.24462	268.15	304.15
$\dot{m}_{air}$ (kg/s)	0.635	0.15554	0.01555	0.38	0.89
$\dot{m}_{water}$ (kg/s)	2.9577	1.20274	0.12027	0.99	4.93
RH_{amb}	0.6	0.24403	0.02440	0.2	1
$\dot{E}xergy_{D,total}(Kj/s)$	5.1143	3.43478	0.34348	0.65	14.48

Table 2
The characteristics and HT of walls and roof.

	Area (m^2)	Area (f^2)	HT (Btu/h.°F)	HT (kj/s.°F)
North wall	29.25	314.85	40.93 × 1.1	11.99 × 1.1
South wall	29.25	314.85	40.93 × 1.1	11.99 × 1.1
West wall	99	1065.62	138.53 × 1.1	40.59 × 1.1
East wall	99	1065.62	138.53 × 1.1	40.59 × 1.1
Roof	143	1539.24	92.36 × 1.1	27.06 × 1.1
Total				145.45

Btu/h = 0.293 J/s [49].

Table 3
The overall heat transfer of growing hall in each month.

Month	Temperature (T) (K)	Set-point (SP) (K)	Difference of temperatures (SP-T)	Overall HT (kj/s)
Jan.	271.81	294.15	22.34	3.25
Feb.	273.92	294.15	20.23	2.94
Mar.	278.67	294.15	15.48	2.251
Apr.	282.8	294.15	11.35	1.65
May.	287.4	294.15	6.75	0.981
Jun.	290.51	294.15	3.64	0.529
July.	292.28	294.15	1.87	0.272
Aug.	292.41	294.15	1.74	0.253
Sep.	289.09	294.15	5.06	0.736
Oct.	284.81	294.15	9.34	1.358
Nov.	278.48	294.15	15.67	2.28
Dec.	274.41	294.15	19.74	2.871

Table 4
Results of energy evaluating.

Hour	Temp. (K)	Energy balance (kj/s)	Consumption of natural gas (m^3/s)	Realised CO_2 (gr/s)
00:00	270.65	0.1825	0.00000424	0.00840
01:00	269.9	0.07345	0.00000171	0.00338
02:00	270.15	0.1098	0.00000255	0.00505
03:00	270.4833	0.158364	0.00000368	0.00729
04:00	*269.15*	*−0.0356*	*−0.00000083*	*−0.00164*
05:00	*269.15*	*−0.0356*	*−0.00000083*	*−0.00164*
06:00	270.65	0.1825	0.00000424	0.00840
07:00	*269.15*	*−0.0356*	*−0.00000083*	*−0.00164*
08:00	*269.15*	*−0.0356*	*−0.00000083*	*−0.00164*
09:00	269.65	0.0371	0.00000086	0.00171
10:00	270.8167	0.206734	0.00000481	0.00951
11:00	273.4833	0.594466	0.00001382	0.02736
12:00	275.9	0.94585	0.00002200	0.04353
13:00	277.65	1.2003	0.00002791	0.05524
14:00	278.9	1.38205	0.00003214	0.06360
15:00	280.15	1.5638	0.00003637	0.07197
16:00	280.15	1.5638	0.00003637	0.07197
17:00	279.15	1.4184	0.00003299	0.06528
18:00	277.9	1.23665	0.00002876	0.05691
19:00	276.4	1.01855	0.00002369	0.04688
20:00	274.65	0.7641	0.00001777	0.03516
21:00	272.65	0.4733	0.00001101	0.02178
22:00	271.9	0.36425	0.00000847	0.01676
23:00	271.4	0.29155	0.00000678	0.01342
Total		13.62511	0.00031686	0.62705

$$\dot{Q}_{load} = \dot{Q}_{walls} + \dot{Q}_{roof} = \left(\sum U_{wall}A_{wall}(T_{hall} - T_3)\right) + U_{roof}A_{roof}(T_{hall} - T_3) \tag{2}$$

where U is heat transfer coefficient of wall, A is the area of walls or roof, T_3 is the ambient temperature and T_{hall} is the indoor temperature of growing hall.

At the end, the output energy from exhaust of hall is calculated by Eq. (3):

$$\dot{Q}_{out} = \dot{m}_5 h \tag{3}$$

where $\dot{m}_5$ is the air flow of exhaust. Now, the energy balance that would remain in hall is calculated by Eq. (4):

$$\dot{Q}_{balance} = \dot{Q}_{in} - (\dot{Q}_{load} + \dot{Q}_{out}) \tag{4}$$

2.3. Exergy analysis

Exergy is defined as available energy based on the second law of thermodynamics [35]. The other definition that can express the nature of exergy is the maximum ability of working in relation to the environment [36]. There is no commonly accepted definition for the exergy efficiency [37]. The following equation (Eq. 5) is used to calculate the exergy efficiency for each component of the system [37]:

$$\psi_{Ex} = \frac{\dot{E}x_{out}}{\dot{E}x_{in}} \tag{5}$$

$\dot{E}x_{out}$ is the output exergy of one component that arises by T_{out}, $\dot{m}_{out}$, and P_{out} and $\dot{E}x_{in}$ is the input exergy of the same component that arises by T_{in}, $\dot{m}_{in}$, and P_{in}. In order to find $\dot{E}x_{in}$ and $\dot{E}x_{out}$, all equations follow one principle. Calculating exergy whether for input or output can be obtained by following equations (Eqs. (6), (7)) [37]:

$$\dot{E}x = \dot{m}(h - h_0 - T_0(s - s_0)) \tag{6}$$

$$\dot{E}x = \dot{m}(C_{pa} + (\omega.C_{pv})).(T - T_0 - (T_0.\ln(T/T_0)) + (\varpi R_a T_0 \ln(P_4/P_0)) + R_a T_0((1 + \varpi)\ln((1 + \varpi_0)/(1 + \varpi)) + \varpi \ln(\varpi/\omega_0)) \tag{7}$$

where ṁ is the flow rate, h is the enthalpy, T is temperature, P is pressure and $T_0(s\text{-}s_0)$ is the specific exergy caused by generated entropy. The last term of Eq. (7) is the specific chemical exergy that is occurred in ventilating unit of HVAC system. The proportionality between specific humidity ratio ω and specific humidity ratio on a molal basis ϖ is given by $\varpi = 1.608\omega$. Furthermore, each system has its own exergy destruction that is calculated by Eq. (8):

$$\dot{E}x_D = \sum \dot{E}x_{in} - \sum \dot{E}x_{out} \tag{8}$$

where $\sum \dot{E}x_{in}$ is the sum of all input exergies to system and $\sum \dot{E}x_{out}$ is the sum of all output exergies to system. All of variables include ṁ, T and P can be effective on exergy and exergy destruction. For all studies on exergy analyzing, the main aim is to reduce the exergy destruction of system. This means that reduction of exergy destruction creates more ability of working to system. In this study, Engineering Equation Solver (EES) was used to perform the project. Based on Fig. 1, there are five points that exergy should be calculated. Accordingly, $\dot{E}x_1$, $\dot{E}x_2$, $\dot{E}x_3$, $\dot{E}x_4$ and $\dot{E}x_5$ were calculated as exergy of each points. $\dot{E}x_1$, $\dot{E}x_3$ and $\dot{E}x_2$, $\dot{E}x_4$ are respectively input and output Exergies of HVAC system and $\dot{E}x_4$ and $\dot{E}x_5$ are respectively input and output exergies of growing rooms. Then, ψ_{Ex} was calculated for $\dot{E}x_1$ and $\dot{E}x_2$ (as exergy efficiency of heating unit of HVAC), for $\dot{E}x_3$ and $\dot{E}x_4$ (as exergy efficiency of ventilating unit of HVAC) and for $\dot{E}x_4$ and $\dot{E}x_5$ (as exergy efficiency of growing hall).

Accordingly, $\dot{E}x_{D,HVAC}$ and $\dot{E}x_{D,Hall}$ were calculated as destruction exergy of HVAC unit and growing hall, respectively and finally the sum of $\dot{E}x_{D,HVAC}$ and $\dot{E}x_{D,Hall}$ was reported as the total exergy destruction of system.

3. Modeling

3.1. Artificial neural network

Multi Layered Perceptron (MLP) neural network was used to develop a prediction model of exergy destruction and energy consumption of studied system as the most popular and most used method among other methods of neural network [38]. Prediction, classification, modeling, signal processing, error filtering and so on [39] are applications of neural network. Receiving the information by corresponding nodes of input layer activates the external nodes and emits a signal to the next layer. Each node of the input layer has unique and one by one connection with each node of the output layer. These signals are passing through the output layer. Each connection between two nodes in two adjacent layers are related to each other by weighting coefficients, that this weights adjusts the signal strength based on the input data [40]. Depending on the strength of the signal, nodes can be stimulated or inhibited. In training of back propagation method, error is determined by comparing the model's output and the desired output and this error is returned to hidden and input layers to the next training processes. The network training operation ends when the error comes down of the specified value by user [39]. Developing of model was performed using the Artificial Neural Network Toolbox in MATLAB in two separate models, one for exergy destruction and the other for energy consumption. Fig. 4 indicates the structure of developed network. Independent variables that were placed in input layer were $\dot{m}_3$ and $\dot{m}_1$ as the flow rate of hot water and air by kg/s, respectively and the variations of ambient temperature by K and ambient Relative Humidity (RH) and the only independent variable was the total exergy destruction. The total data were divided into two categories. One for training and the second for testing data. As previously was said, the data of sixteen days were applied to training process. The training process was conducted with different numbers of neurons in the hidden layer and the function of each parameter was measured with respect to the base parameter, so that in first stage of training process, the network was trained with one neuron on hidden layer and in next stages the number of neurons were added. In each training process of network, weights and biases were corrected to reduce tilt of performance function and the output matrix of network was obtained. For a certain neurons in the hidden layer, different results may be obtained in each training process. Therefore, training process for each number of neurons on hidden layer was done in three repetitions and the value of performance function (Mean Square Error (MSE)) was calculated for each repetition and the average value of performance function for three repetitions was obtained. Calculating the average value eliminates the effect of the output difference (Table 5).

3.2. Adaptive neuro fuzzy inference system (ANFIS)

In this section, a prediction model of system was developed using ANFIS method. Structure of an adaptive network contains a number of nodes that are connected through directional links. These adaptive nodes make the outputs using on modifiable parameters. Learning rules are responsible for minimizing error by updating parameters [41]. ANFIS uses fuzzy logic and neural network systems and constructs a hybrid intelligent system with advantages of both fuzzy logic and neural networks [42]. ANFIS has five layers [38,43,44] (Fig. 5):

- Layer 1. This layer gets the inputs of fuzzy system and introduces to ANFIS model.
- Layer 2. This layer gets the output of first layer and decides about fuzzy rules based on prior values of MFs that have received by the first layer.
- Layer 3. This layer normalizes the degree of activity of any rules.
- Layer 4. This layer adopts the nodes and provides a primary model using functions.
- Layer 5. This layer gets the outputs of layer 4 and prepares them as output values of network.

The ANFIS model was developed for prediction of total exergy destruction of system using ANFIS toolbox on MATLAB software. Input parameters were $\dot{m}_3$ and $\dot{m}_1$ as the flow rate of hot water and air in kg/s, respectively and the variations of ambient temperature by K and ambient Relative Humidity (RH), and the output of model was the total exergy destruction. The network was trained with two numbers of membership functions. Selecting the type of membership functions are the main part of training process. In order to select the type of membership function, training of networks was performed with g bell, gauss and trap types of membership functions and the performance parameters were calculated for each type (Table 5). The types of output membership functions were selected linear type because of its ability to further reduce of errors. Training of FISs was performed with hybrid optimum method and 0 value of error tolerance.

4. Evaluation of developed models

The evaluation and comparing performance of MLP and ANFIS models were performed by comparing the results of the output of networks and target values using Root Mean Square Error (RMSE), Pearson correlation coefficient (R), mean absolute error (MAE) and mean square error (MSE) as follow [38,45]:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(A-P)^2 \tag{9}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A-P)^2} \tag{10}$$

$$R = \left(1-\left(\frac{\sum_{i=1}^{n}(A-P)^2}{\sum_{i=1}^{n}A_i^2}\right)\right)^{1/2} \tag{11}$$

$$MAE = \frac{\sum_{i=1}^{N}|A-P|}{N} \tag{12}$$

where A is the target value and P is the predicted value [46]. The RMSE was used to calculate the difference between the predicted and target values. Decreasing the difference between output and target values decreases the RMSE value. The Pearson correlation coefficient (r) was used for expressing linear correlation between actual and predicted values and is as a measure of the degree of linear dependence between two variables [1].

5. Results and discussions

This section presents the results of study which has four stages. The first stage presents the results of energy analyses and discussions. The

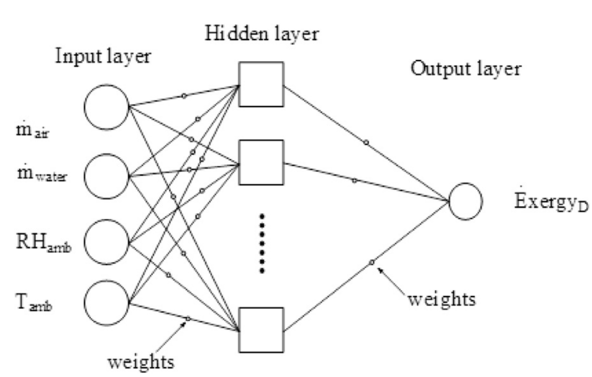

Fig. 4. Structure of MLP network.

Table 5
The results of selecting the best predictor model.

ANFIS		MLP	
Type of MFs	MSE	Number of neurons	Average MSE
Guass.	*0.000614*	8	0.0761
Trap.	0.0829	*10*	*0.0154*
G bell.	0.0174	12	0.3413

second stage focuses on exergetic analyses. The third one presents the modeling results and the last one discusses the pollution and economic costs and effect of the developed models.

Table 1 demonstrates the primary results of recorded data that is obtained by analyzing the samples using T-test with IBM SPSS Statistics 19 software.

Based on Table 1, T_{amb} is varying from 268.15 to 304.15 K that has the mean value of 285.35 K by deviation of 12.44 K. The $\dot{m}_{air}$ was changed from 0.38 to 0.89 kg/s by variation of input air flow of HVAC. It has the mean value of 0.635 kg/s by deviation of 0.155 kg/s. The variation of $\dot{m}_{water}$ is in range of 0.99–4.93 kg/s by deviation of 1.202 kg/s. This variation was performed by variation of input water flow of HVAC heating coils. From the other hand, the variation of RH_{amb} for the studied region, based on meteorology data was a range of 0.2–1, approximately. By combining these parameters as independent variables of study, the total exergy destruction of system was calculated from 0.65 to 14.48 KJ/s. This parameter has the mean value of 5.1143 KJ/s by deviation of 3.434 KJ/s and standard mean error of 0.343.

5.1. Energy analysis

Energy analysis was performed on various values of T_{amb} with the aim of discussing on the effect T_{amb} on required heating energy to keep the indoor temperature in the desired range. It is require calculating the HT based on the coefficient of the construction materials of production hall. The construction materials that were used to build the hall are mainly solid brick with thickness of 16″ (40.6 cm) with plastered on furring with thickness of 1″ (2.5 cm) for walls that has the heat transfer coefficient (HTC) equal to 0.13 (Btu/h.ft^2.°F) [47,48] and for the roof of hall is from concrete with gypsum board with thickness of 12″ (30 cm) that has the HTC equal to 0.06 (Btu/h.ft^2.°F) [47,48]. Table 2 presents the characteristics and HT of walls and roof.

The HT values were multiplied to 1.1 in order to obtain heat load. Multiplying HT values to difference temperature of indoor and outdoor obtains the overall heat transfer of growing hall in different ambient temperatures.

Table 3 illustrates that the values of HT are require for holding the indoor temperature at 294.15 K and it is clear that the maximum overall HT belongs to Jan (3.25 kj/s) and the minimum value is for Aug (0.253 kj/s). It means that between coldest and warmest season of year there is a difference about 3 kj/s for one growing mushroom hall. The reported number of heating value of natural gas in references is about 43,000 kj/m^3 [50]. So, the difference of coldest and warmest season is a value about 0.07 × 10^{-3} m^3/s for one growing hall in this study. The fuel of natural gas has more than 96% of methane in Iran. Therefore, it is equal to about 0.0672 × 10^{-3} m^3/s of methane. Using fossil energy for economic activities from manufacturing to agricultural industries, results in GHG emissions in almost all region of the world [51]. One kg of fuel combustion of methane releases 2.875 kg of carbon dioxide in stoichiometric condition (Eq. (13)):

$$CH_4 + \frac{2}{0.21}(0.21O_2 + 0.79N_2) \rightarrow CO_2 + 2H_2O + \frac{2 \times 0.79}{0.21}N_2 \tag{13}$$

The density of methane is 0.717 kg/m^3, so it will be equal to 0.0481 gr/s of methane. CO_2 is the most unwanted gases among GHG emissions caused by energy production [52]. The related released CO_2 will be 0.138 gr/s.

Based on the collected data, Table 4 was prepared to demonstrate the energy evaluation. Table 4 shows the values of $\dot{Q}_{in}$, $\dot{Q}_{load}$ and $\dot{Q}_{out}$ The negative sign is defect of energy and positive sign is surples of energy. The basis of calculations is the average ambient temperature of four days (previously was said as validation data-set) of week that was recorded by related temperature sensor (Fig. 3).

Based on the results, the value of energy balance is negative at temperature of 269.15 K. it is clear that at this temperature, the system is unable to supply the required heating energy. On other temperatures, there are excess of energy. The italic numbers on values relative the temperature of 269.15 K indicate that the value of natural gas was consumed less and related CO_2 emission was prevented. Based on Table 4, by increasing the ambient temperature, the values of excess energy has been increased such that at the temperature of 280.15 K is reached to its maximum value (1.5638 kj/s). As an initial result, it can be said that one of the reasons in arising this issue is the lake of precies controlling system and the system is controlled manually by operator. By adding the values of surplus energy, it was calculated that there was 13.7675 kj/s of energy losses that was equal to 3.201 × 10^{-4} m^3/s of natural gas and production of 0.633 gr/s of CO_2. The price of 1 m^3 of natural gas in Iran is about 0.05 $ [53]. Therfore this energy losses is equal to 1.6 × 10^{-5} $/s for one mushroom production hall that is equal to about 41.49 $ more cost for one month.

5.2. Exergy analyses

Exergy analysis was performed using EES software. Therefore, the independent variables of study were considered as the parameter that can affect the exergy destruction and exergy efficiency. Accordingly, after importing the required equations in EES, the values of exergy destruction of each component, exergy efficiency of HVAC unit and generated exergy of each component were exported. Then, by importing experimental data, the trends of each dependent variable were investigated. Fig. 5 indicates the results of exergy destruction of system against the energy balance of system by changing temperature. Fig. 6 shows the exergy destruction and exergy efficiency of HVAC system. These parameters are displayed in one chart in order to compare them.

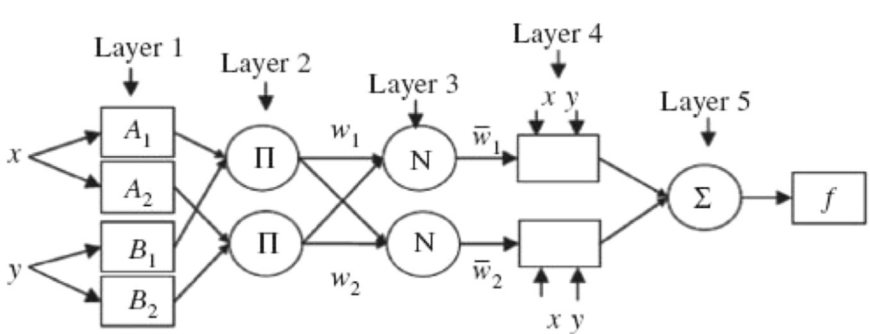

Fig. 5. General structure of ANFIS model.

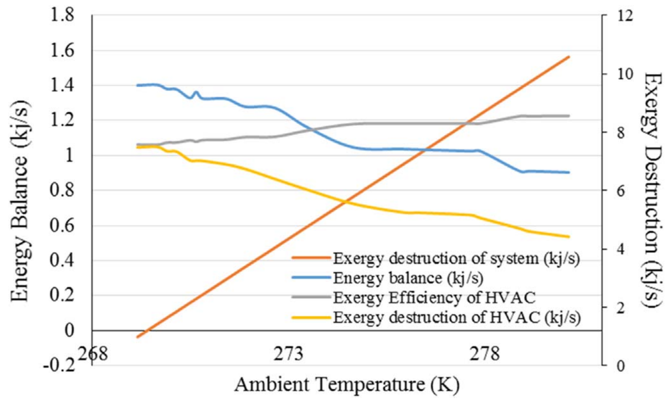

Fig. 6. The results of exergy destruction of system.

Therfore, due to range of exergy efficiency that is between 0 to 1 and is a small range comparing to exergy destruction, it was normalized between 0 and 10 by multiplying to 10, only to enlarge the range of data for a better comparison.

Fig. 6 illustrates the maximum destruction of exergy which was occurred when the energy balance was negative. It means that for this condition the system could'nt supply the required thermal energy, and this condition is for low values of ambient temperature. For this condition, the exergy destruction of HVAC system is maximum and consequently the exergy efficiency of HVAC system is minimum. Increasing ambient temperature, increases the energy balance of system and exergy efficiency of HVAC system and accordingly decreases the exergy destruction of system and HVAC unit. Based on the definition of exergy, this means that increasing ambient temperature and accordingly increasing the value of Energy balance increases using the energy opportunity and provides the energy efficiency and decreases the energy losses. At the highest value of temperature, the maximum energy balance and maximum efficiency of HVAC and minimum exergy destruction were gained. But variation of ambient temperature is not a controlable parameter and is natural. For achieving the optimum condition in term of exergy analyzing, there is a need to define system based on controlable parameters.

Based on experimental data, there was a centeral boiling unit for fourty growing halls. Each growing hall was at different stages of crop growth, so each growing hall had the different thermal requirements. The temperature of centeral boiling unit was hold in constant value and accordingly it was unable to be changed for one growing hall. Therefore, the flow rate of input air and input hot water were the parameters that could be controlled. Fig. 7 indicates the system behavior with changing $\dot{m}_{air}$ and $\dot{m}_{water}$ at constant values of ambient and water temperatures.

Fig. 7(a, c and e) are related to variation of exergy destruction of system and exergy efficiency of HVAC based on flow rate of air as independent variable. Fig. 7(b, d and f) are related to variation of independent variables by flow rate of water. Fig. 7(a and b) are the surface of variations. In order to do better analysis, the countours of Fig. 7(a and b) was presented in Fig. 7(c and d). Fig. 7(c) shows that for outside of a specified range, increasing the flow rate of air, increases the exergy destruction of system and exergy efficiency while these is a contradictory issue about two parameters. On the other hand, Fig. 7(d) shows that increasing flow rate of water increases exergy efficiency of HVAC and decreases exergy destruction of system. The variation of these parameters have a nonlinear trend.

Fig. 7(e and f) indicate the optimum values of air and water flow, respectively and system behavior against the flow rate of air and water that were calculated by response surface method (RSM) in Design Expert software. Optimization was performed with the aim of maximizing exergy efficiency of HVAC system and minimizing the total exergy destruction. Therefore, 0.8553 kg/s of air flow and 0.001 m^3/s (about 1 L/s) of water flow are the best and optimal values to reach the maximum accessible exergy efficiency of HVAC and minimum exergy destruction of system.

6. Modeling

6.1. Training process

Modeling process was performed by the MLP and ANFIS methods. To perform modeling operations, total exergy destruction of system was considered as the independent variable (output of network). Also, air flow rate, water flow rate ambient relative humidity, and ambient temperature were considered as independent variables (inputs of network).

During the modeling operations, 10 neurons in the hidden layers for MLP network (Table 5) and Gaussian membership function for ANFIS network (Table 3) provided the best and highest performance (lowest MSE) and precies output values. In process of selecting the best number of neurons in hidden layer for MLP network and the best type of membership function of ANFIS network, the networks gain the best response when the performance function's values for training data are at their lowest value. Accordingly, after training by different number of neurons in the hidden layer for MLP network and by different types of membership function for ANFIS method, 10 numbers of neurons were selected as the best numbers of neurons for MLP network and Gaussian type of membership function for ANFIS method (Table 5).

The training of MLP network was performed in three repetition and the value of MSE was calculated for each repetition and its average value was reported. This can eliminate the effect of the output difference in each repetition.

6.2. Testing process

In order to develop model, the validation data-set of energy analyzing were imported to models. This can evaluate the exergy destruction of system in parallel to energy analysis and help to analyze system. Accordingly, Table 6 was prepared to indicate the results of training and testing, numerically.

Deviation is the sum of differences between target and output values of developed models based on exergy destruction with unit of kj/s. Increasing deviation between target and output values of models, increases the exergy and energy loss. Therfore, system losses or the chance of useful work Would be negligible.

In training process (Table 6), there is no significant difference between the results of MLP and ANFIS methods. Such that the linearity of ANFIS's outputs with target values is 0.9999 and the linearity of MLP's outputs with target values is 0.9992. This conclusion also is true about deviation values. For training process, the loss of useful energy (deviation value) is 0.3547 kj/s for ANFIS method that is equal to 0.825×10^{-5} m^3/s of natural gas, 1.632×10^{-2} gr/s of CO_2 and 4.125×10^{-7} \$/s of more cost. If we calculate this numbers for one month, we will have 919.3 Mj loss of useful energy, 21.38 m^3 more consumption of natural gas, 42.31 kg CO_2 emission and 1.07\$ more cost. The loss of useful energy of MLP network in training process is 0.7362 kj/s and this value is equal to 1.712×10^{-5} m^3/s of natural gas, 3.388×10^{-2} gr/s of CO_2 and 8.56×10^{-7} \$/s of more cost. Accordingly, for one month it will have 1908.23 Mj loss of useful energy, 44.377 m^3 more consumption of natural gas, 87.82 kg of CO_2 emission and 2.21 \$ more cost. But the performance of modeling depends on the responses of models in testing stage. The responses of models can be measured by performance factors. After importing the testing data (Table 6) the results was a little different compared to the results of training process. Such that, ANFIS with linearity of 0.9982 and RMSE of 0.0681 had the best performance with deviation of 0.9694 kj/s that is equal to 2.254×10^{-5} m^3/s of natural gas, 4.461×10^{-2} gr/s of CO_2 and 11.272×10^{-7} \$/s of more cost compared to MLP method that has linearity of

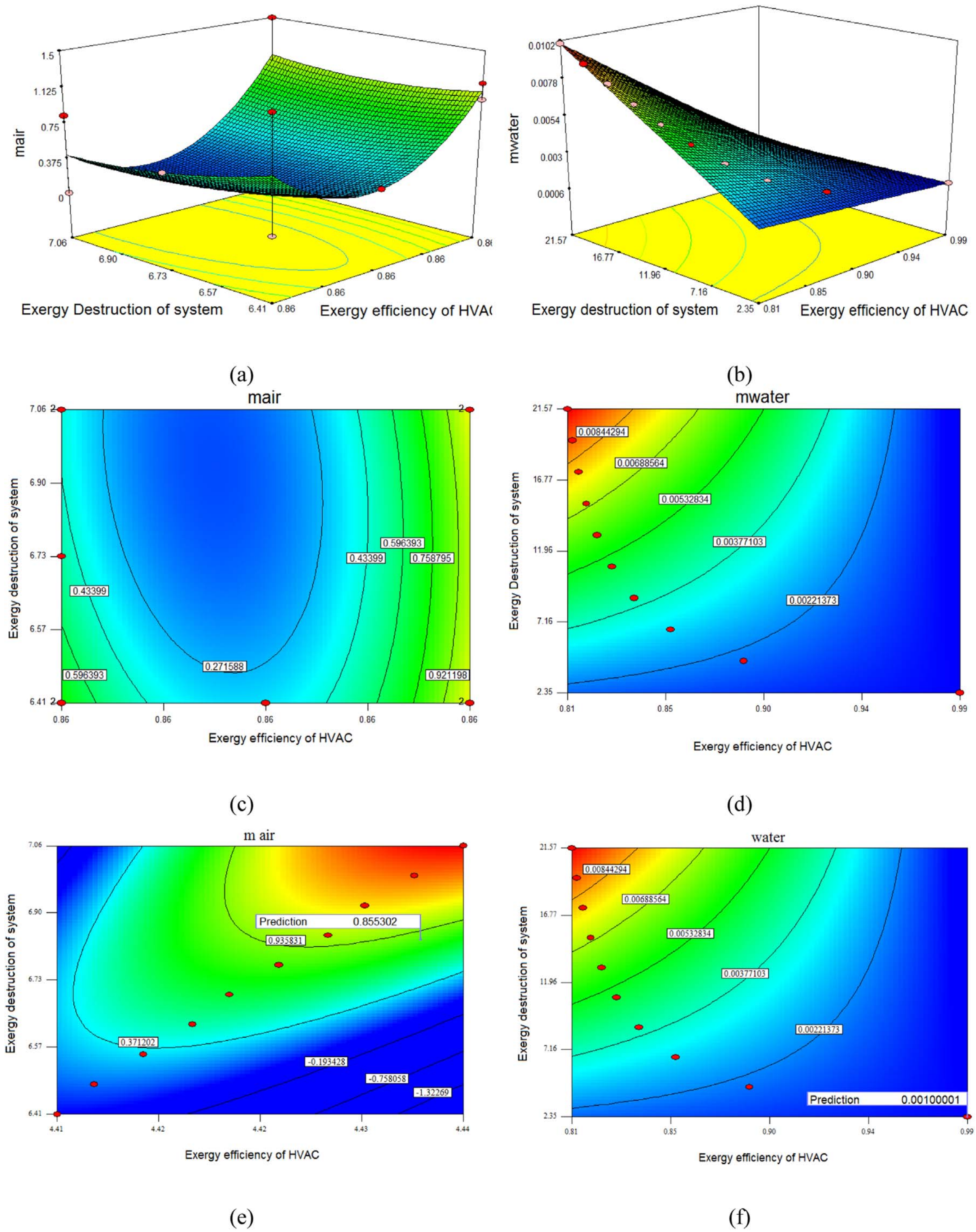

Fig. 7. The system behavior by variation of controllable parameters.

Table 6
The results of training and testing processes.

	Training process				Testing process			
	R	RMSE	MAE	Deviation (kj/s)	r	RMSE	MAE	Deviation (kj/s)
ANFIS	0.9999	0.0248	0.01496	0.3547	0.9982	0.0681	0.0402	0.9694
MLP	0.9992	0.1202	0.03106	0.7362	0.9511	0.5584	0.5218	12.5254

0.9511 and RMSE of 0.5584 with deviation of 12.5254 kj/s that is equal to 29.13 × 10^{-5} m^3/s of natural gas, 0.576 gr/s of CO_2 and 1.456 × 10^{-5} $/s of more cost. This is a considerable value of energy loss and CO_2 emission of MLP network compared to ANFIS method. This comparision shows the ability of ANFIS method in prediction of exergy destruction and modeling of studied system compared to MLP network. Fig. 8 presents this claim, visually. There are several studies that reported the high ability of ANFIS as predicting tool. The ability of ANFIS in case of application on energy consumption was studied by Ekici et al. [54] to predict energy consumption of building in a cold region. The objective of this paper is to examine the feasibility and applicability of ANFIS in building energy load forecasting area. Based on the results it was observed that ANFIS can be a strong tool to predict the energy consumption in buildings. Soyguder et al. [55] studied Adaptive Network Based Inference System (ANFIS) model on HVAC system. Based on their results, ANFIS could predict the performance of HVAC system with a high accuracy.

As seen on Fig. 8(a), it is clear the trend of variation of target values against the predicted values is devient as 9.54% from linear trend, by Eq. (14) [31].

$$\text{Devient from linearity} = ((1 - R^2) \times 100) \tag{14}$$

This deviation causes 11.556 kj/s more energy consumption and 0.5318 gr/s of CO_2 emission of MLP compared to ANFIS. In one month it will cause 29.95 Gj more energy consumption and 1.378 t emission of CO_2. This claim is also considerable from Fig. 9.

Fig. 9 shows that the MLP has a trend with obvious distance from target value. If the system be placed in a control circuit, the system will try to reach a steady state and to overcome the current error, so the system will change the inputs, constantly. This creates loss of time and failure of system on MLP model compared to ANFIS model. The result of this operation will yield to energy losses, cost rising and accordingly would have more GHG emission by consuming more energy. Table 6 illustrates that by using MLP there would be 11.556 kj/s more energy compared to ANFIS, imposes 1.343 × 10^{-5} $/s more cost (34.83 $ for one month) and 2.687 × 10^{-4} m^3/s more consumption of natural gas (696.58 m^3 for one month). Therefore, applying ANFIS model prevents energy, time, cost losses and more GHG emission, so it can be the best and suitable model to adopts in real system.

7. Conclusion

According to the main aim of the present study on exergy destruction, the study was developed using experimental data from one of the mushroom growing farms. The results of this study are presented as followings:

- Gaussian Mf type with performance of 0.000614 was selected for ANFIS method and 10 neurons on hidden layer with performance of 0.0154 was selected for MLP network.
- In training process, there is no significant difference between the results of MLP and ANFIS methods and there is a close value of difference of target and output values of methods.
- By importing the testing data the results have been a little different compared to the results of training process.
- ANFIS with linearity of 0.9982 and RMSE of 0.0681 had the best performance with deviation of 0.9694 kj/s that is equal to 2.254 × 10^{-5} m^3/s of natural gas, 4.461 × 10^{-2} gr/s of CO_2 and 11.272 × 10^{-7} $/s of more cost.
- MLP method had a poor performance in this study by linearity of 0.9511 and RMSE of 0.5584 with deviation of 12.5254 kj/s that is equal to 29.13 × 10^{-5} m^3/s of natural gas, 0.576 gr/s of CO_2 and 1.456 × 10^{-5} $/s of more cost.

Therefore, this comparision shows the ability of ANFIS method in prediction of exergy destruction and modeling of studied system compared to MLP network. So, If the system be placed in a control circuit, applying ANFIS model prevents energy, time, cost losses and more GHG emission, so it can be the best and sustainable model to adopt in real system.

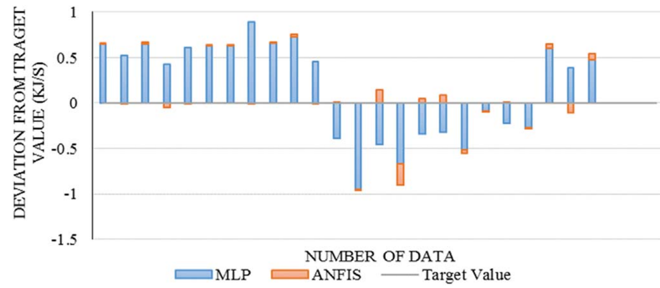

Fig. 9. The results of deviations from target values for developed models.

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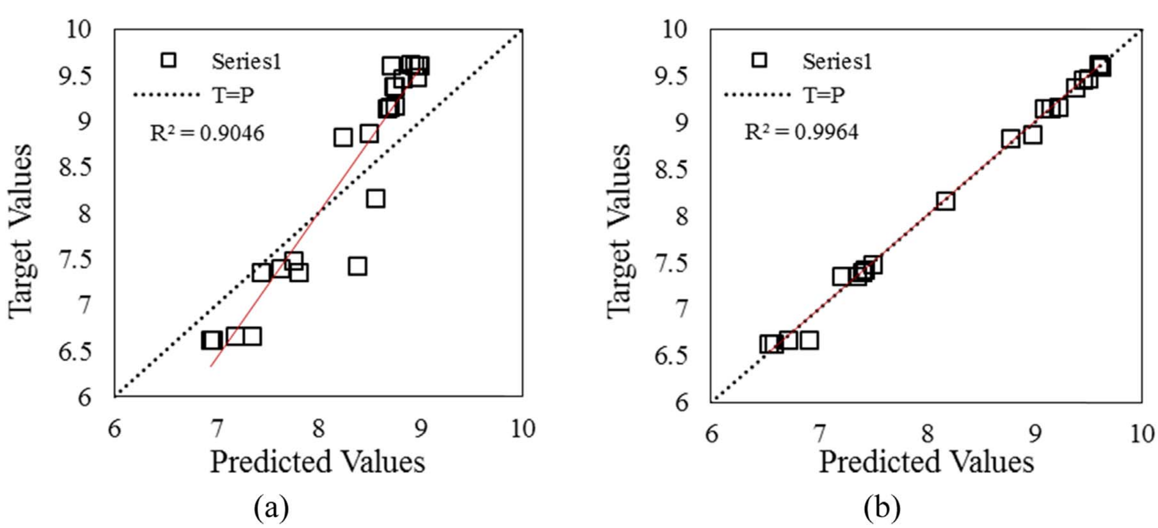

Fig. 8. The results of testing the models. a. MLP b. ANFIS.

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