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RESEARCH ARTICLE

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Factors affecting energy consumption and productivity in greenhouses

Mohammad Younesi-Alamouti[1], Hamid Khafajeh[2] and Mohammad Zarein[2]

[1] Agricultural Research, Education and Extension Organization (AREEO), Imam Khomeini Higher Education Center, Karaj, Iran. [2] Tarbiat Modares University, Biosystems Engineering Dept., Tehran, Iran.

Abstract

Aim of study: To investigate the impact factors affecting the greenhouse environment on energy consumption and productivity.

Area of study: Alborz province of Iran during the period 2018–2020.

Material and methods: In this study, 18 active units of greenhouse owners in Alborz province of Iran that had necessary standards were identified. Then, upper and lower amplitudes of the variables affecting productivity and energy consumption in greenhouses were calculated using a type-2 fuzzy neural network, Matlab 2017 software. Area, temperature, energy exchange, environmental evapotranspiration and relative humidity were studied as indicators.

Main results: With each unit of temperature, energy consumption and productivity increased by 0.737% and 0.741%, respectively; with each unit of energy exchange, they increased by 0.813% and 0.696%, respectively; with each unit of evaporation and transpiration of the environment, they increased by 0.593% and 0.869%, respectively; and with each unit of humidity, they increased by 0.398% and 0.509%, respectively.

Research highlights: The factors affecting the greenhouse environment such as area, temperature, evapotranspiration and relative humidity had a significant effect on productivity in studying greenhouses and therefore increasing their productivity. According to the results, the model's ability in energy consumption was better than that for energy efficiency prediction. Also, greenhouse ranking was done by FAHP method.

Additional key words: temperature; environment evapotranspiration; relative humidity, fuzzy neural network.

Abbreviations used: AHP (Analytic Hierarchy Process); ANN (Artificial Neural Network); BP (Back-Propagation); FAHP (Fuzzy Analytic Hierarchy Process); FLS (Fuzzy Logic Systems); MADM (Multiple Attribute Decision-Making); MAE (Mean Absolute of Errors); MODM (Multiple Objective Decision Making); MLP (Multi-Layer Perceptron Network); MSE (Mean Square of Errors); RMSE (Root Mean Square of Errors).

Authors' contributions: Analysed and interpreted the data: HK. All authors conceived and designed the research, wrote the paper and approved the final manuscript.

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Correspondence should be addressed to Mohammad Zarein: m.zarein@modares.ac.ir

Introduction

Increasing production and competitiveness has led to developing new methods in greenhouses and their products. In recent years, new methods have been applied in greenhouses for improvement of the automation to increase performance and improve product quality (*e.g.*, He & Xue, 2011). The greenhouse industry is one of the growing sectors in agriculture, and therefore an increase in energy consumption is predicted in this industry. Due to the high cost of energy in many countries, many studies have been conducted to develop different methods to reduce energy consumption in the greenhouse (Pilkington *et al.*, 2010). The main environmental factors contributing to the greenhouse climate are temperature, relative humidity of the inside air, vapor pressure deficit, transpiration sunlight, CO_2 concentration, air movement, and lighting (Shamshiri *et al.*, 2018). Measuring and controlling the high number of effective parameters in plant growth, evaluation and monitoring of the greenhouse conditions, and planning for optimal energy and water consumption can easily be done by computer controlled systems (Jones Jr, 2016). Multiple attribute decision-making (MADM) techniques, unlike multiple objective decision making (MODM), heavily involves human participation and judgments. Research on human judgments and decision making shows that the human brain can consider only a limited amount of information at any one time (Simpson, 1996), which makes it unreliable to take decisions when facing complex problems. This enables users to extract benefits from all the combined methods and achieve the desired goal in a better way. As a practical popular methodology for dealing with fuzziness and uncertainty, the Fuzzy Logic combined with Analytic Hierarchy Process (AHP), more commonly known as Fuzzy AHP or FAHP (Van-Laarhoven & Pedrycz, 1983), has found huge applications in recent years. Kubler *et al.* (2016) reviewed the state of the art on FAHP applications. Also, the sustainability of greenhouse structure (Tunnel or Canarian) was studied in Biskra, Algeria using AHP (Bencheikh *et al.*, 2017). The regional factor on the improvement of technical efficiency and technological innovation seems to be very important; also due to regional inequalities, more research is needed on the economic, social and geographical characteristics of products (Hsu *et al.*, 2003). Djevic & Dimitrijevic (2009) studied the effect of four different double plastic covered greenhouses on energy efficiency in winter lettuce production in Serbia. Results showed that the lowest energy consumption (9.76 MJ/m^2) was obtained for multi-span greenhouse. Canakci & Akinci (2006) investigated the greenhouse energy consumption and production, and found that the energy efficiency ratio for the four main crops of greenhouse (tomato, pepper, cucumber, and eggplant) was 0.32, 0.19, 0.31 and 0.23, respectively. In another study conducted by Hatirli *et al.* (2006) for greenhouse required energy of chickpeas, the consumed energy of diesel, chemical fertilizer, electricity and human were 34.3%, 27.5%, 16.1%, 1.10%, 6.8%, respectively. Murthy *et al.* (2009), studied technical efficiency and its determinants in tomato production in Karnataka, India, that found medium-sized greenhouses are at the best level in terms of technical efficiency. Ozkan *et al.* (2011) examined energy use patterns in Antalya province, Turkey, and the relationship between energy inputs and yield for single crop (winter) greenhouse tomato production. The results indicated that the bulk of energy was consumed in fertilizer (38.22%), electricity (27.09%), manure (17.33%) and diesel-oil (13.65%). Average yield and energy consumption were calculated as 57,905.1 kg/ha and 61,434.5 MJ/ha, respectively.

The greenhouse environment is affected by various variables outside and inside the greenhouse, such as unstable environmental conditions and the shape of the structure. Greenhouse energy and efficiency have a great impact on the efficiency of a greenhouse. In this work, we studied the effect of factors affecting the greenhouse environment such as area, energy exchange, temperature, evapotranspiration and relative humidity on energy consumption and productivity, using the neural network method. Also, the ranking of greenhouse based on energy consumption and productivity was done by using the hierarchical process of fuzzy analysis (FAHP) method.

Material and methods

This field study describes the sample properties and then generalizes these features to the statistical population. In fact, this research is a survey type. Survey research describes, predicts, and analyzes the relationship among variables. Eighteen active units of greenhouse owners in Alborz province of Iran that had the necessary standards were identified. Then, to determine the preferences of different users, we distributed a questionnaire between the managers of these greenhouses to collect the initial information and measurement tools of the sample. Each group of respondents filled in 18 questions under the presence of the questioner and the average of each group's preferences was considered as the basis of the work. Then, using the Type-2 Fuzzy Neural Network in Matlab 2017 software, we calculated the high and low amplitudes of effective variables such as area, temperature, energy exchange, evapotranspiration and humidity on energy efficiency and energy consumption in greenhouses. Regarding the greenhouse owners´age, 5.8% were < 30 years old, 65.8% were between 30 and 50 years old, and 28.4% were > 50 years old, the average being 43.93 years old. In terms of education, the results showed that 50% of the respondents had a diploma or less, 22.22% a bachelor degree, 16.17% a master of science degree, and 11.11% a Ph.D. or higher. Regarding experience in greenhouse cultivation, 50% of greenhouse owners had < 10 years, 34% were between 11 and 20 years and 16% > 20 years.

Type-2 fuzzy logic systems

Type-2 fuzzy sets are finding very wide applicability in rule-based fuzzy logic systems (FLSs) because they model uncertainties whereas such uncertainties cannot be modeled by type-1 fuzzy sets. A block diagram of a type-2 FLS is depicted in Figure 1 (Castro *et al.*, 2008). The fuzzy system includes the steps of specification of the controller inputs and outputs; fuzzification; fuzzy rule base; and defuzzification.

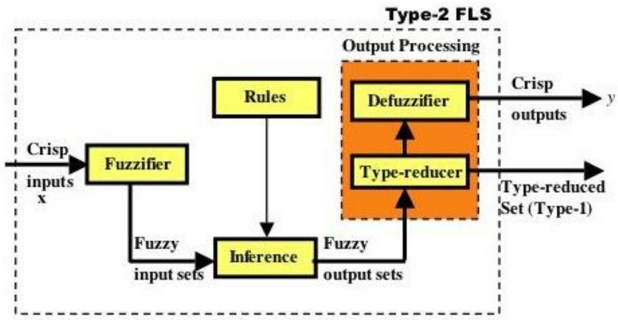

Figure 1. Scheme of type-2 fuzzy logic system (FLS). *Source:* Castro *et al.* (2008).

Determination of neural network type

The neural network used in this study is a multi-layer perceptron network (MLP) with an error back-propagation algorithm. MLP is a kind of networked subsystem. In the perceptron network, the neurons are placed in successive layers. When the input data is applied to the network, the first layer calculates its output values and replaces them on the next layer input. The next layer receives these values as inputs and transfers its output values to the next layer (Escamilla-Garcia *et al.*, 2020). The error-recurrence network Back-Propagation (BP) is used to analyze nonlinear issues and predictions. In the BP algorithm, the network output and the actual or target value were compared with each other, the error resulting from each repetition of the training set was calculated and returned to the network input to weigh the bias, and the network parameters were designed to optimize its performance. Next, it provided a more correct output and, as a result, the network error (from the mean square error –MSE– value) was reduced and minimized (Han *et al.*, 2021). Error-returning neural network is one of the most widely used types of neural networks, which can be considered as a multiple regression analysis that can analyze complex and nonlinear data. The learning algorithm of error-returning is the most powerful learning algorithm for teaching multi-layer perceptron training (Patil *et al.*, 2008). Figure 2 shows a neural network of a kind of backpropagation (Erb, 1993). There are many types of research in different fields, including engineering, economics and management, which use the backpropagation network to predict errors. Among them, Moon & Son (2021) pointed out that the multi-layered backbone network utilized error-returning algorithms to predict customer satisfaction.

Determination of neural network topology

The neural network of this study has an input layer with three neurons and an output layer with three neurons. There is no specific rule about the number of hidden layers and the number of its neurons, which can be determined by trial and error. Increasing the number of hidden layers leads to the computational complexity of the network and therefore leads to increasing the training time (Hsu *et al.*, 2003). Moon & Son (2021) have pointed that the number of hidden layer neurons can be in the range [m (n+1), 2n+1], where n is the number of neurons in the input layer and m is the number of neurons in the output layer. Therefore, we applied one hidden layer with 10 neurons.

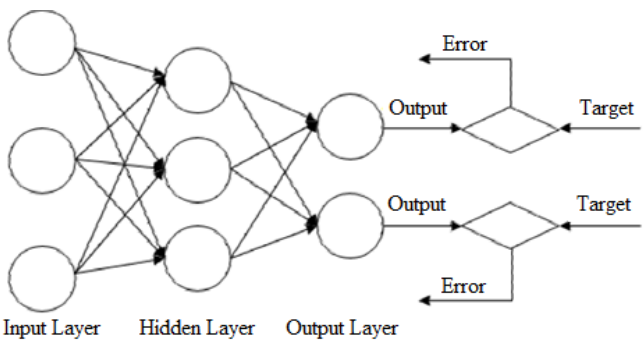

Figure 2. Schematic neural network of a kind of back propagation. *Source*: Erb (1993).

Determination of neural network parameters

The purpose of implementing a returning-error propagation network is to balance the offset and generalizability. The training set continues until reduction the error to reach a minimum value. The network begins to disassociate when the error begins to increase and at the same time the learning process stops. The rule used for learning an error-return backpropagation network is the type of generalized delta learning, and in this case, the mean square error rate is reduced (Reynolds *et al.*, 2018). In this research, three types of errors were investigated including Mean Square of Errors (MSE), Root Mean Square of Errors (RMSE) and Mean Absolute of Errors (MAE). Another network parameter is the activation function which used to calculate the output of the neuron. The activation functions are both linear and nonlinear, but nonlinear activation functions were used in multi-layer networks because of making the hidden layer more powerful. The sigmoid function is the most common and popular function used in error-returning networks (Reynolds *et al.*, 2018). This function can generalize the learning characteristics and increase the accuracy of the model (Jin *et al.*, 2000). The Levenberg-Marquardt was used as a network learning algorithm which is the best recommended learning algorithm (Wilamowski, 2009). A summary of the used parameters network in this study is shown in Table 1.

Results and discussion

Type-2 Fuzzy was used for the calculations and its input and output membership functions are defined in Figure 3. In this research, the input and output membership functions were considered as combination types of triangular-Gaussian. So, the left and right shapes are the same. But the input values which were defined by experts, are different to these functions. Type-2 Fuzzy is defined as two functions. The value of first function is 1, and the value of the second function was expressed as fuzzy. This second assignment functions also have a

Table 1. Summary of the network parameters used in this study

Parameters	Explain	Symbol
Network type	Multi-layer perceptron	MLP
Number of input layer neurons	3	N_i
Number of output layer neurons	3	N_o
Number of hidden layers	1	N_{hl}
Number of hidden layer neurons	10	N_h
Training algorithm	Back-propagation	BP
Training function	Levenberg-Marquardt	LM
Training rule	Generalized delta	GD
Transfer function	Sigmoid	Sig
Error evaluation	mean square error	MSE
	root mean square error	RMSE
	mean absolute error	MAE

value in the range of 0 to1. This value can have a specific value for each input variable, such as x between the upper and lower limits. In this case, each batch function covers a limited space with one boundary at the top and bottom. The area between these two boundaries is called the FOU (Uncertainty Trail). This area of the community is made up of all possible values for belonging performance. These types of belonging functions are called base belonging functions. The color difference shows the same upper and lower limit. Figures 4a, 4b, and 4c show the triangular, Triangular-semi Gaussian and Triangular- Gaussian input functions, respectively. According to Figures 4a, 4b and 4c, triangular-Gaussian fuzzy input functions have the highest coverage of uncertainty. Type-2 Fuzzy system has more ability to cover uncertainties than Type I. Utilization of transfer function with more ability to cover the uncertainties is preference.

Therefore, we have calculated the Type-2 Fuzzy using MATLAB software. Table 2 has been elaborated based on the information of 10 questionnaires selected by the active elite in the capital market. In this table, the average of 10 experts' opinions was considered as input data of the fuzzy logic method. Since different users have different preferences, different indices for greenhouses are not equally important. Thus, the FAHP model was used to determine greenhouse preferences and reduce ambiguity and lack of confidence. The ratios used to evaluate the performance of greenhouses are also presented in Table 2.

In this study, the data of the pairwise comparison matrix were considered as Gaussian triangular, where b is the middle dimension, a and c are the left and right values of the Gaussian triangular fuzzy number, respectively. The greenhouse preferences were obtained in Table 3 using the data of distributed questionnaires for different groups and proportions in a comparative manner:

At first, according to the FAHP method, the combined value of the criteria was calculated using the pairwise matrix, which is as follows:

$$S_{c_1} = (1.74 , 1.98 , 11.4) \otimes (0.0117 , 0.0214 , 0.0389) = (0.0203 , 0.0214 , 0.0389)$$

$$S_{c_2} = (1.75 , 5.29 , 11.77) \otimes (0.0117 , 0.0214 , 0.0389) = (0.0204 , 0.1134 , 0.4756)$$

$$S_{c_3} = (1.93 , 5.68 , 16) \otimes (0.0117 , 0.0214 , 0.0389) = (0.0225 , 0.1218 , 0.6221)$$

$$S_{C4} = (10.90 , 16.91 , 23.22) \otimes (0.0117 , 0.0214 , 0.0389) = (0.1273 , 0.3626 , 0.9028)$$

$$S_{C5} = (9.40 , 16.78 , 23.22) \otimes (0.0117 , 0.0214 , 0.0389) = (0.1098 , 0.3598 , 0.9028)$$

Then, calculations related to the magnitude of each of the combined values were obtained. The results were presented as follows:

$$V(S_{c_1} \geq S_{c_2}, S_{c_3}, S_{c_4}, S_{c_5}) = \min(0.856 , 0.841 , 0.497 , 0.512) = 0.497$$

$$V(S_{c_2} \geq S_{c_1}, S_{c_3}, S_{c_4}, S_{c_5}) = \min(1.194 , 0.981 , 0.570 , 0.585) = 0.570$$

$$V(S_{c_3} \geq S_{c_1}, S_{c_2}, S_{c_4}, S_{c_5}) = \min(1.152 , 1.014 , 0.673 , 0.683) = 0.673$$

$$V(S_{c_4} \geq S_{c_1}, S_{c_2}, S_{c_3}, S_{c_5}) = \min(1.569 , 1.393 , 1.377 , 1.004) = 1.004$$

$$V(S_{c_5} \geq S_{c_1}, S_{c_2}, S_{c_3}, S_{c_4}) = \min(1.561 , 1.387 , 1.371 , 0.996) = 0.996$$

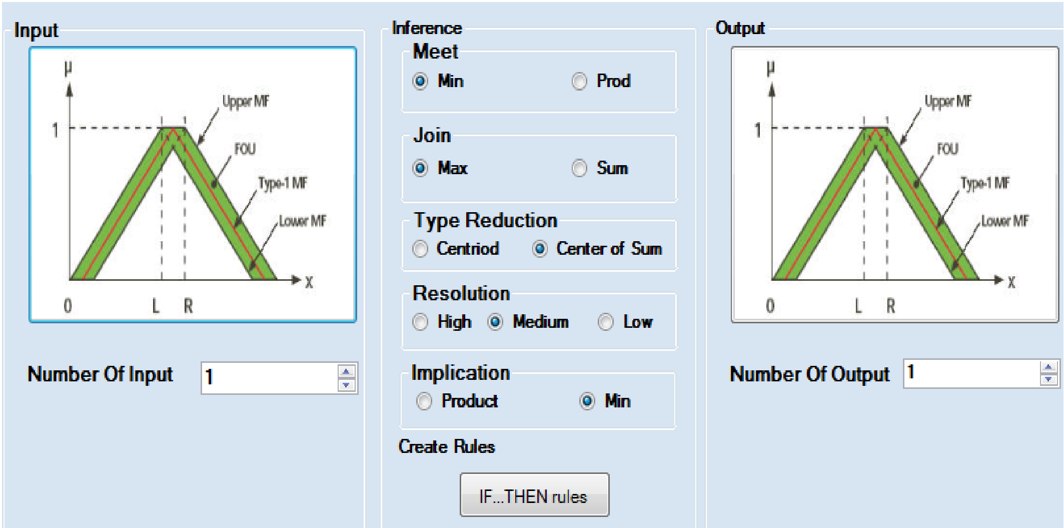

Figure 3. Input data for calculations of type-2 Fuzzy system

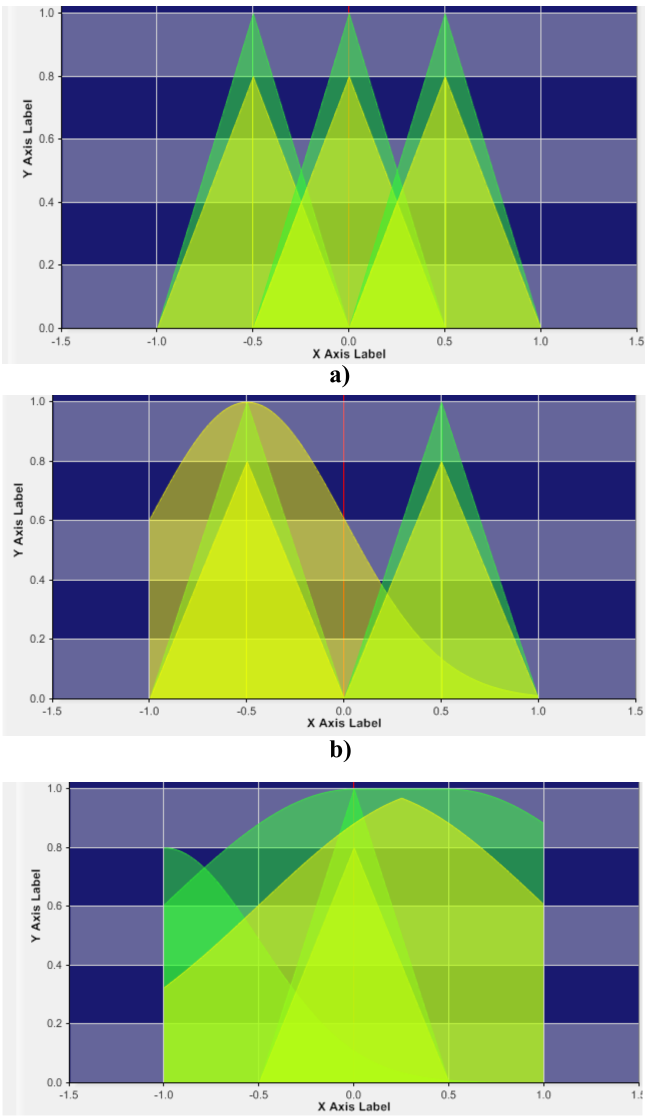

Figure 4. Triangular input: (a) semi Gaussian input, (b) Gaussian input and (c) fuzzy function

Finally, weighted non-normal values of each main indicators were calculated as follows:

$$\acute{w} = (0.497\,, 0.570\,, 0.673\,, 1.004\,, 0.996)^T$$

Then, the normalization process was used to normalize of non-normal weights of main indices.

$$W = (0.1328\,, 0.1524\,, 0.1799\,, 0.2684\,, 0.2665)^T$$

In Table 4 the values for each indicator are presented for each greenhouse. Also, the greenhouses were ranked using the AHP approach. The value of the score for each greenhouse and its rank are reported in Table 4.

An ANN model with four sub-categories as sub-model was created to estimate of efficiency and energy consumption of greenhouses, in which the data of 12 and 6 greenhouses were considered as training and testing sets, respectively. In other words, in each sub-instance, 6 samples of the training set are replaced with 6 samples of the other experimental set. The results of model estimation at different states are reported in Table 5.

According to the results, the model's ability in energy consumption was better than that for energy efficiency prediction.

The effect of variables on energy consumption and greenhouse productivity are presented in Table 6. Energy consumption and productivity in the greenhouse were increased with area per unit by 0.613% and 0.653, respectively. Consequently, due to the greater effect of area on productivity than energy consumption, the efficiency of the area index is recommended to increase greenhouse efficiency. An increase in temperature led to an increasing in energy consumption and productivity by 0.737% and 741%,

Table 2. The ratios used to evaluate the greenhouses performance

Main index	Secondary index	Explain	Value
C_1: Area (m^2)	A_f	Greenhouse floor area	4.21
	A_s	Greenhouse coverage area	4.35
C_2: Temperature (°C)	T_{ai}	Inside greenhouse temperature	4.27
	T_{ao}	Outside greenhouse temperature	4.19
	T_m	Thermal mass temperature	3.87
	a	building solar thermal efficiency	4.64
C_3: Power exchange (W)	Q_{cc}	Conduction and convection	4.02
	Q_m	Thermal mass	3.88
	Q_e	Product evapotranspiration	4.66
	Q_n	Energy losses due to foggy conditions	4.18
	Q_v	ventilation by the window	4.49
C_4: Environment evapotranspiration (kgH_2O/s)	ET	Product evapotranspiration	4.31
	Fog	Water fog system	4.13
C_5: Moisture (g/kg)	X_{ai}	Absolut moisture of inside greenhouse	4.16
	X_{ae}	Absolut moisture of outside greenhouse	3.45
	X_{sat}	Saturation moisture	4.77
	H_{ai}	Relative humidity of inside greenhouse	4.16
	H_{ao}	Relative humidity of outside greenhouse	3.87

respectively. Also, the efficiency of the temperature index is recommended to increase greenhouse efficiency. As each unit of energy exchange increased, energy consumption and productivity were increased by 0.813% and 0.696%, respectively. The energy exchange index is not recommended to increase greenhouse efficiency because its efficiency is more than energy consumption. Increasing each unit of evaporation and transpiration, led to an increase of 0.595% for energy consumption and 0.886% for productivity. The efficiency of the environmental evapotranspiration index is recommended to increase greenhouse efficiency. Also, an increase in humidity increased the energy consumption and productivity by 398% and 509%, respectively. The efficiency of the moisture index is recommended to increase greenhouse efficiency.

In summary, the purpose of this study was to evaluate and rank active greenhouses using indicators affecting the productivity and energy consumption of greenhouses by the FAHP method. Then, using the Type-2 Fuzzy, we will calculate the high and low amplitude of variables affecting energy efficiency and consumption in greenhouses. Other objectives of this study were to obtain the effect of variables of area, temperature, energy exchange, evapotranspiration and relative humidity on energy consumption and greenhouse productivity by neural network method. The results showed that in variables where the productivity is more than energy consumption, the efficiency of those variables is suitable for increasing greenhouse productivity. Also, the accuracy of the neural network in predicting energy consumption is higher than the energy efficiency.

Table 3. Paired comparison matrices of indicators to each other from the point of view of decision makers

Index	C_1	C_2	C_3	C_4	C_5
C_1	(1, 1, 1)	(0.32, 0.35, 7)	(0.14, 0.33, 3)	(0.14, 0.15, 0.20)	(0.14, 0.15, 0.20)
C_2	(0.14, 2.89, 3.11)	(1, 1, 1)	(0.33, 1, 7)	(0.14, 0.20, 0.33)	(0.14, 0.20, 0.33)
C_3	(0.33, 3, 7)	(0.14, 1, 3)	(1, 1, 1)	(0.32, 0.35, 1)	(0.14, 0.33, 5)
C_4	(5, 6.89, 7.11)	(3, 5, 7)	(1, 2.89, 3.11)	(1, 1, 1)	(0.90, 1.13, 5)
C_5	(5, 6.89, 7.11)	(3, 5, 7)	(0.20, 3, 7)	(0.20, 0.89, 1.11)	(1, 1, 1)

Table 4. The values of each indicator and score for each greenhouse

Greenhouse	Moisture	Evapotranspiration	Energy exchange	Temperature	Area	Score	Rank
1	0.0719	0.0080	0.0307	0.0302	0.0216	0.1316	18
2	0.0358	0.0841	0.0494	0.0285	0.0292	0.3942	14
3	0.0659	0.0319	0.0188	0.0360	0.0125	0.5191	4
4	0.0125	0.1001	0.0223	0.0360	0.0483	0.4102	11
5	0.0071	0.0660	0.0308	0.0298	0.0125	0.5350	2
6	0.0726	0.0628	0.0378	0.0359	0.0174	0.5263	3
7	0.0073	0.0562	0.0333	0.0318	0.0075	0.6048	1
8	0.0472	0.0323	0.0501	0.0324	0.0087	0.4464	8
9	0.0118	0.0811	0.0408	0.0290	0.0162	0.4331	9
10	0.0103	0.1018	0.0262	0.0254	0.1030	0.5147	5
11	0.0968	0.0267	0.0573	0.0342	0.0140	0.4894	7
12	0.0610	0.0480	0.0260	0.0312	0.0095	0.5042	6
13	0.0173	0.0670	0.0225	0.0268	0.0312	0.4289	10
14	0.0245	0.0273	0.0340	0.0370	0.0046	0.3985	13
15	0.0093	0.0342	0.0162	0.0361	0.0084	0.3371	12
16	0.0613	0.0784	0.0194	0.0321	0.0146	0.2634	16
17	0.0487	0.0521	0.0183	0.0345	0.0057	0.2184	17
18	0.0633	0.0646	0.0307	0.0266	0.0085	0.3371	15

Table 5. Results of model performance in energy consumption and efficiency prediction

	Model 1: Energy consumption				Model 2: Greenhouse productivity			
	Sub-model				Sub-model			
	1	2	3	4	1	2	3	4
True predicted (No.)	79	82	80	84	78	76	78	79
True predicted (%)	94	98	95	100	93	90	93	94

Table 6. The effect of variables on energy consumption and greenhouse productivity

Variables	Energy consumption (%)	Greenhouse productivity (%)
Area	61.3	65.3
Temperature	73.7	74.1
Energy exchange	81.3	69.6
Evapotranspiration	59.3	86.9
Moisture	39.8	50.9

References

Bencheikh A, Nourani A, Chabaca MN, 2017. Sustainability evaluation of agricultural greenhouse structures in southern of Algeria using AHP, case of study: Biskra province. Agric Eng Int CIGR J 19: 56-64.

Canakci M, Akinci I, 2006. Energy use pattern analyses of greenhouse vegetable production. Energ 31: 1243-1256. https://doi.org/10.1016/j.energy.2005.05.021

Castro JR, Castillo O, Melin P, Rodríguez-Díaz A, 2008. Building fuzzy inference systems with a new interval type-2 fuzzy logic toolbox. In: Transactions on computational science I. Springer, Berlin. pp: 104-114. https://doi.org/10.1007/978-3-540-79299-4_5

Djevic M, Dimitrijevic A, 2009. Energy consumption for different greenhouse constructions. Energ 34: 1325-1331. https://doi.org/10.1016/j.energy.2009.03.008

Erb RJ, 1993. Introduction to backpropagation neural network computation. Pharm Res 10: 165-170. https://doi.org/10.1023/A:1018966222807

Escamilla-Garcia A, Soto-Zarazúa GM, Toledano-Ayala M, Rivas-Araiza E, Gastélum-Barrios A, 2020. Applications of artificial neural networks in greenhouse technology and overview for smart agriculture development. Appl Sci 10 (11): e3835. https://doi.org/10.3390/app10113835

Han X, Wei Z, Zhang B, Li Y, Du T, Chen H, 2021. Crop evapotranspiration prediction by considering dynamic change of crop coefficient and the precipitation effect in back-propagation neural network model. J Hydrol 596: e126104. https://doi.org/10.1016/j.jhydrol.2021.126104

Hatirli SM, Ozkan B, Fert C, 2006. Energy inputs and crop yield relationship in greenhouse tomato production. Renew Energ 31: 427-438. https://doi.org/10.1016/j.renene.2005.04.007

He H, Xue H, 2011. The design of greenhouse environment control system based on variable universe fuzzy control algorithm. V Int Conf on Computer and Computing Technologies in Agriculture, Berlin (Germany), pp: 72-78. https://doi.org/10.1007/978-3-642-27281-3_10

Hsu SH, Yu MM, Chang CC, 2003. An analysis of total factor productivity growth in China's agricultural sector. Am Agr Econ Assoc, Working paper 01/2003.

Jin W, Li ZJ, Wei LS, Zhen H, 2000. The improvements of BP neural network learning algorithm.V Int Conf on Signal Processing Proceedings, Beijing (China), Aug 21-25. pp: 1647-1649.

Jones Jr JB, 2016. Hydroponics: a practical guide for the soilless grower. CRC Press, Florida, USA. 440 pp.

Kubler S, Robert J, Derigent W, Voisin A, Le-Traon, Y, 2016. A state-of the-art survey & testbed of fuzzy AHP (FAHP) applications. Exper Syst Appl 65: 398-422. https://doi.org/10.1016/j.eswa.2016.08.064

Moon T, Son JE, 2021. Knowledge transfer for adapting pre-trained deep neural models to predict different greenhouse environments based on a low quantity of data. Comput Electron Agric 185: e106136. https://doi.org/10.1016/j.compag.2021.106136

Murthy DS, Sudha M, Hegde MR, Dakshinamoorthy V, 2009. Technical efficiency and its determinants in tomato production in Karnataka, India: Data Envelopment Analysis (DEA) Approach. Agric Econ Res Rev 22: 215-224.

Ozkan B, Ceylan RF, Kizilay H, 2011. Energy inputs and crop yield relationships in greenhouse winter crop tomato production. Renew Energ 36: 3217-3221. https://doi.org/10.1016/j.renene.2011.03.042

Patil SL, Tantau HJ, Salokhe VM, 2008. Modelling of tropical greenhouse temperature by auto regressive and neural network models. Biosyst Eng 99: 423-431. https://doi.org/10.1016/j.biosystemseng.2007.11.009

Pilkington LJ, Messelink G, Van-Lenteren JC, Le-Mottee K, 2010. Protected biological Control-Biological pest management in the greenhouse industry. Biol Cont.52: 216-220. https://doi.org/10.1016/j.biocontrol.2009.05.022

Reynolds J, Rezgui Y, Kwan A, Piriou S, 2018. A zone-level, building energy optimisation combining an artificial neural network, a genetic algorithm, and model predictive control. Energ 151: 729-739. https://doi.org/10.1016/j.energy.2018.03.113

Shamshiri RR, Jones JW, Thorp KR, Ahmad D, Che-Man H, Taheri S, 2018. Review of optimum temperature, humidity, and vapour pressure deficit for microclimate evaluation and control in greenhouse cultivation of tomato: a review. Int agrophys 32: 287-302. https://doi.org/10.1515/intag-2017-0005

Simpson L, 1996. Do decision makers know what they prefer?: MAVT and ELECTRE II. J Oper Res Soc 47: 919-929. https://doi.org/10.1057/jors.1996.117

Van-Laarhoven PJM, Pedrycz W, 1983. A fuzzy extension of Saaty's priority theory. Fuzz Set Syst 11: 229-241. https://doi.org/10.1016/S0165-0114(83)80082-7

Wilamowski BM, 2009. Neural network architectures and learning algorithms. IEEE Ind Electron Mag 3: 56-63. https://doi.org/10.1109/MIE.2009.934790