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MODELING OF ENERGY CONSUMPTION OF CUCUMBER GREENHOUSES USING ARTIFICIAL NEURAL NETWORK AND ANFIS

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نمذجة استهلاك الطاقة للبيوت المحمية بالخيار باستخدام الشبكة العصبية الاصطناعية و ANFIS

ملخص

الاستخدام الأمثل للطاقة هو حاجة أساسية للزراعة المستدامة. ومع ذلك ، زيادة الطلب بالنسبة للغذاء ، زاد استهلاك الطاقة في القطاع الزراعي. لأن القطاع الزراعي جزء أساسي من تحويل الطاقة هو أننا نركز على تقييم كفاءة الخيار الدفيئات الزراعية في مقاطعة الأذربايجان الشرقية من قبل ANNIS و .ANFIS لذلك ، تم أخذ العينات من خيار الدفيئة ، وتم جمع البيانات باستخدام استبيان المقابلة. وأخيرا، المدخلات والطاقة الناتجة ، مؤشرات الطاقة واستهلاك الطاقة من الدفيئة الخيار تقييم ونمذجة. من بين المدخلات ، كان للوقود والحبوب أعلى وأدنى حصة قدرها 37/55 إجمالي استهلاك الطاقة بين 23−5−10−5 ونتائج نمذجة الطاقة ، على التوالي أظهر الاستهلاك أن R2 لـ RBF و MLP و ANFIS كانت 96 و 87 و 89 و 39.7 ٪ على التوالي. لذلك شبكة RBF أفضل.

Abstract

Optimal use of energy is a key requirement for sustainable agriculture. However, the growing demand for food has increased the energy consumption of the agricultural sector. Since the agricultural sector is the main sector of energy conversion, we focused on evaluating the efficiency of cucumber greenhouses in East Azerbaijan Province by artificial neural network and ANFIS. So, 135 cucumber producing greenhouses were sampled, and data were collected with an interview questionnaire. Finally, the inputs and output energy, the energy indices and the energy consumption of cucumber greenhouse was assessed and modeled. Among the inputs, fuel and seed had the highest and lowest share of 55.37 and 23×10^{-5} % in total energy consumption, respectively. The results for the modeling of energy consumption revealed that R^2 was 96, 87, 89, and 39.7% for RBF, MLP, ANFIS, respectively. So, RBF network could predict energy consumption of the greenhouses with the least error.

1. INTRODUCTION

Iran is the third leading cucumber producer of the world with an annual production rate of 1.8 million tons after China and Russia [1]. The growing interest of foreign investors to construct greenhouses in Iran in recent years on the other hand have laid ground to shift crops with high water demand from farms to controlled environments like greenhouses because crops consume less water and produce more in greenhouses, and this improves water efficiency and is more economical. Energy is the key component of economic development. So, energy scarcity is a serious limitation hindering the development of low-income countries [2]. The energy of agricultural production inputs can be divided into two main categories: direct energy and indirect energy. Direct energy refers to the energy that directly leads to a work or an effort at farms. Examples of direct energy resources are labor, the energy content of fuels, electricity, and irrigation energy. Indirect energy is the type of energy consumption to produce inputs before their application at farms, such as energy consumption to produce the fertilizers, herbicides, and manure. The main indirect use of energy in agricultural production is associated with fertilizers, especially nitrogen [3]. Nonrenewable energy resources include the diesel, chemical herbicides, chemical fertilizers, electricity, and machines, whereas renewable energy resources encompass the labor, seeds, irrigation water, and manure [4].

The assessment and modeling of energy consumption in a greenhouse are among the main issues that should be considered in checking. Presently, it is crucial to estimate energy use of the agricultural sector, especially greenhouses correctly. The selection of a sound modeling technique can contribute to predicting energy consumption more accurately. Mathematical models are extensively used to find out practical relationships between inputs and outputs of a production process. But this classic reasonable approach requires a precise definition of mathematical model equations to describe the events. So, today we witness the growing tendency to the use of intelligent calculational methods, e.g. fuzzy logic, artificial neural networks (ANN), and adaptive neural-fuzzy inference system [5].

Artificial neural network (ANN)[1] models are nonlinear models that can estimate any relationship between inputs and outputs with any desired precision if an appropriate structure is applied. By this structure, we mean the number of neurons, hidden layers, and activation functions. Adaptive neural-fuzzy inference system (ANFIS) encompasses a set of IF-THEN rules and fuzzy input-output data pairs and employs ANN learning algorithms for training [6].

Multiple regressions are a statistical method used in modeling using independent and dependent variables. The precision of these three methods in a forecast process is compared by RMSE[2] and R[2(3)]. It should be noted that the lower the RMSE is and the higher the R2 is, the more precise the model will be. Mohammadi and Omid (2010) conducted an economic analysis of the relationship between the input and output energy of greenhouse cucumber production in Iran [7]. They reported that 148,836.7 MJ ha^{-1} energy was, on average, consumed to produce 1 kg greenhouse cucumber.

Fossil fuel and chemical fertilizers accounted for the highest share of energy consumption (41.94 and 19.67%, respectively) in Tehran County. Average energy productivity was estimated at 0.80 kg MJ^{-1} and the ratio of output energy to input energy at 0.64.

Sanei Moghadamet al. (2010) investigated the energy consumption for greenhouse cucumber production systems in Mashhad County [8]. Average energy consumption to produce 1 kg greenhouse cucumber was found to be 1.2 and 0.9 MJ in autumn and spring, respectively. Furthermore, the highest energy consumption in cucumber greenhouses was captured by fossil fuel, electricity, and labor, respectively. In another study, rain fed pea energy and yield were modeled and analyzed in Bokan County [9]. They used ANFIS to forecast the rain fed pea energy consumption and yield with a bell-shaped membership function and a hybrid learning algorithm and estimated R^2 at 94.2 and 96.7% for energy consumption and yield, respectively. In another study, Taghavifar and Mardani (2015) modeled energy consumption and pollution emission in apple production process using ANNs and found the 8-16-2 topology to be the best structure for energy consumption (R2 = 0.99) and pollution emission (R2 = 0.98) [10].

Asfandari- kenari et al. (2016) explored the input and output energy of cucumber production in the greenhouses of Tehran Province [11]. They calculated total input energy and output energy to be 153,819 and 80,638.59 MJ ha^{-1}, respectively, and fuel, electricity, and chemical fertilizer had the highest shares of 72.69, 10.95, and 10.37% in total input energy, respectively. Boland Nazaret al. (2015) studied input and output energy of greenhouse cucumber production in Jiroft County, Iran [12]. They found the total input and output energy to be 296,601.4 and 156,800 MJ ha-1, respectively. Fuel, electricity, and chemical fertilizer were the main constituents of the total input energy, accounting for 60.38, 16.12, and 12.19% of it, respectively. A similar study was conducted in Isfahan Province, Iran by Heidari et al. (2012). They found that the total input and output energies were 141.40 and 77.88 GJ ha-1, respectively with diesel and nitrogen fertilizer having the highest shares of 54.17 and 15% in total input energy, respectively [13]. In a study on input and output energies of soil-based and hydroponic cucumber greenhouses in Western Azerbaijan Province, Iran, Portaraudi et al. (2015) concluded that the total input and output energies were 16877756.99 and 326000 MJ ha^{-1} in the soil-based greenhouses and 16634562.3 and 587333.3 MJ ha^{-1} in the hydroponic greenhouses [14]. In both greenhouses, fuel and electricity formed the greatest part of input energy so that their share in total input energy was 93.93 and 5.15% in the soil-based greenhouses and 92.72 and 6.52% in the hydroponic greenhouses, respectively.

The output energy of greenhouse and field cucumbers were modeled on the basis of energy consumption pattern using ANN and ANFIS by Haji Agha Alizadeh et al. (2016) [15]. The results revealed that the fuzzy method outperformed the neural networks and the R2 value was calculated at 0.9924 and 0.9920 for ANFIS modeling of energy consumption in greenhouse

[1] - Artificial Neural Networks
[2] - Root Mean Square Error
[3] - Coefficient of determination

and field cucumber production systems, respectively. Nonetheless, R2value was 0.9492 for the application of neural networks to greenhouse cucumbers with the optimal 1-10-8 topology and 0.9785 for field cucumbers with the optimal 1-12-8 topology, implying the good capability of both models to estimate the output energy. Taki and et al. (2012) investigated the energy consumption of corn silage and modeled its output energy with multilayer feed-forward neural network [16]. They reported that the best model had an 8-5-5-1 structure with two hidden layers. In their attempt to model energy consumption and greenhouse gases (GHG) emission in wheat farms of Isfahan Province, Khoshnevisan et al. (2013) found that the neural network model with 11 input parameters, including of land size and input energies, and two hidden layers with five neurons could simultaneously forecast the two output parameters, i.e. output energy and GHG emission rate, with a very high precision and very low error [17]. Pahlavan et al. (2012) focused on analyzing input-output energy and applying ANN to the forecast of basil production [18]. Energy consumptions of the inputs were included as the model input. They demonstrated that the model with a 7-20-20-1 structure could predict the basil yield with a high precision. To the best knowledge of the authors, no research has ever been undertaken to use ANNs and ANFIS to forecast the energy consumption in cucumber greenhouses of East Azerbaijan Province, Iran. So, the present study models the energy consumption of the greenhouses in this region with a multilayer perceptron (MLP) neural network, radial basis function (RBF), and ANFIS system.

2.MATERIALANDMETHODS

Since the statistical population was large in East Azerbaijan Province, it was sampled. The sample size was determined by Cochran's formula as Equation (1) [19] according to which 135 greenhouses were sampled from all cucumber greenhouses in the studied region. Data were collected from the greenhouse owners by a questionnaire through one-on-one interviews.

$$n = \frac{Nt^2S^2}{Nd^2 + t^2s^2}$$

Which N denotes the size of the statistical population or the number of farmers in the studied region, t is the acceptable coefficient of confidence that is derived from the t-student table assuming the normal distribution of the intended trait, S is an estimate of the variance of the trait in the population, d is the optimal probable precision (half of the confidence interval), and n is the sample size. Finally, 135 cucumber greenhouses with almost uniform environmental and planting conditions were sampled. Data were collected from the farmers using face-to-face interviews. The data collected belonged to the production period of 2017–2018.

2.1. ENERGY CONSUMPTION OF CUCUMBER GREENHOUSES

The cucumber greenhouse input energy (MJ ha-1) included the machinery, human labor, fuel (natural gas), herbicides, water for irrigation, electricity, seed, farmyard manure (FYM), nitrogen (N), phosphate (P_2O_5), potassium (K_2O) and micronutrient fertilizers and the output energy was from cucumber yield (kg ha-1). Energy equivalents of these inputs and output were obtained by using of energy coefficients (Table 1). The total input equivalent can be calculated by adding up the energy equivalents of all inputs in Mega Joule (MJ).

TABLE 1. Energy coefficients of different inputs and output

Inputs	Unit	Energy coefficients (MJ unit-1)	Reference
A. Inputs			
1. Machinery	h	9	[20]
2. Human labor	h	1.96	[20]
3. Fuel (Natural gas)	m3	49.5	[20]
4. Herbicides	kg	120	[21]
5. Water for irrigation	m3	1.02	[22]
6. Electricity	kWh	11.93	[23]
7. Seed	kg	1	[23]
8. FYM	kg	0.3	[24]
9. Nitrogen (N)	kg	66.14	[22]
10. Phosphate (P2O5)	kg	12.44	[22]
11. Potassium (K2O)	kg	11.15	[22]
12. Micro (M)	kg	120	[22]
B. Out put			
Cucumber	kg	0.8	[7]

2.2. ANN MODELS

The first step was the selection of network dimensions in the simulation of energy consumption of cucumber greenhouses in East Azerbaijan Province using two neural network models: multilayer perceptron (MLP) and radial basis function (RBF). We used the MATLAB 2012 software package to model by MLP and RBF networks. The best structure considered for these two networks to forecast the output energies based on input energies is illustrated in Figure 1.

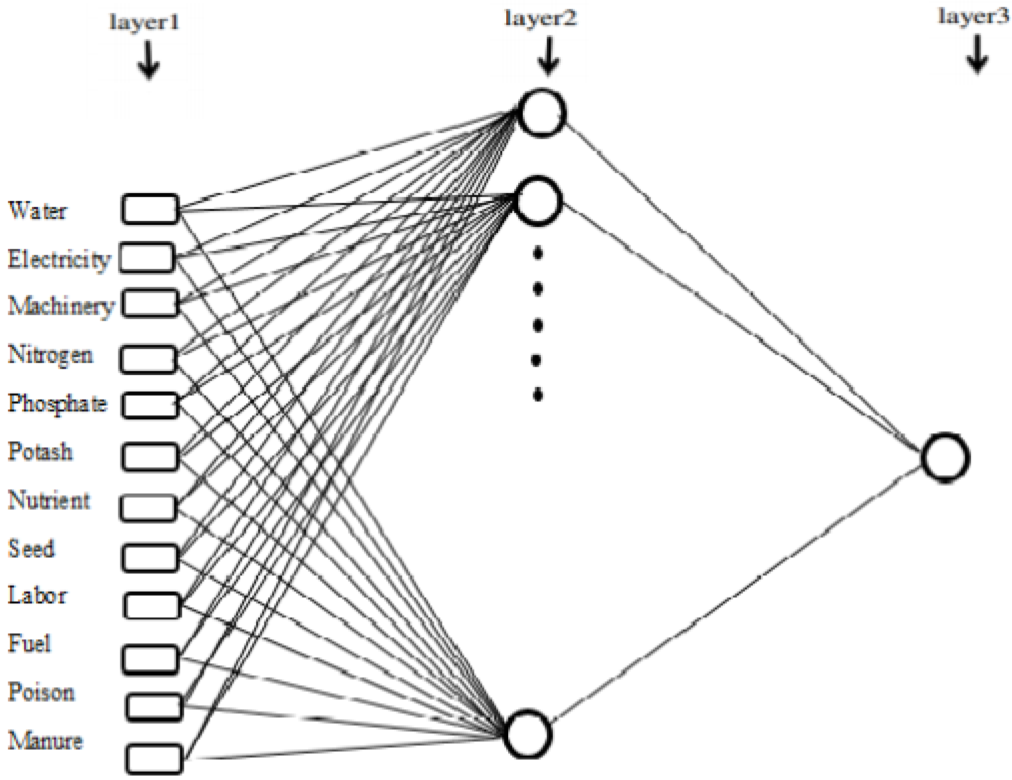

Figure 1. The best structure of MLP and RBF models to forecast the energy consumption of cucumbers produced in greenhouses

2.3.ANFIS

The AFNIS model encompasses both neural networks and fuzzy models. The fuzzy phase establishes the relationship between inputs and outputs, and the parameters pertaining to the membership functions of the fuzzy phase are determined by the neural networks. So, the features of both fuzzy and neural models are embedded in ANFIS.

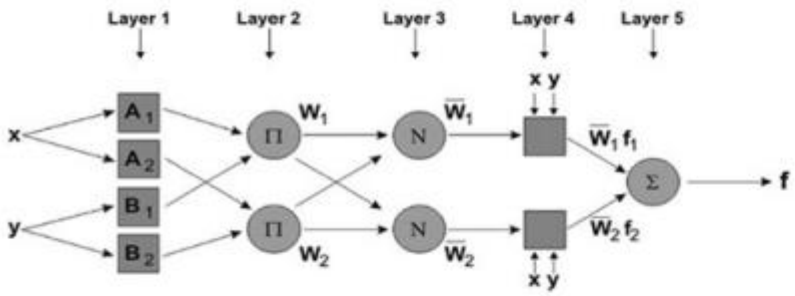

Figure 2. The structure of the ANFIS model

2.4.MULTIPLEREGRESSION(SMLR)

Regression is a statistical procedure to explore and model the relationship of variables. In analyses addressing crop production, multiple regressions is a commonly used statistical technique as more than one independent variable is required to forecast the value of a dependent variable.

Here, we explain the multivariate regression model. Let $X1$, $X\ 2$, $X\ 3$,K, $X\ q$ be the constant independent variables and y be the dependent variable that can be shown by the following regression model.

$Y = \beta 1 + \beta 1X\ 1 + \Lambda + \beta\ qX\ q + \varepsilon$ (2)

In the present study, we employed the coefficient of correlation (R), relative mean error (RME), and root mean square error (RMSE) to evaluate the accuracy of the forecast models. They can be estimated by Equations (3)-(5) [22].

$$R = \sqrt{1 - \frac{(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} \hat{y}_i^{\,2}}} \tag{3}$$

$$RME = \frac{1}{n}\sum_{i=1}^{n} \frac{y_i - \hat{y}_i}{y_i} \times 100 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)} \tag{5}$$

in which P is the predicted value, A is the actual observed value for the i-farmer and n is the number of observation. Readers can refer to the literature for further details on ANFIS and the functions used in this method [23].

3. RESULTS AND DISCUSSION

Table 2 presents the consumption quantity of input and output, their energy equivalent, and their share in accounting for total input energy of greenhouse cucumber production in the studied region.

TABLE 2. The quantity and pattern of input energy consumption for cucumber production

	Unit	Consumption rate (unit/ha)	Energy equivalent (MJ/ha)	Percent (%)
Inputs				
1. Fuel	m3	4008.148	198403.13	55.37
2. Electricity	kWh	6834.36	81533.97	22.75
3. Labor	h	13872.49	27190.09	7.58
4. Manure	kg	45751.9	13725.57	3.83
Chemical fertilizer				
5. Nitrogen	kg	865.15	17537.333	4.89
6. Phosphate	kg	716.22	2192.28	0.61
7. Potash	kg	293.85	3276.52	0.91
8. Micronutrients	kg	58.14	6977.06	1.94
9. Herbicides	kg	35.23	4227.73	1.18
10. Seed	kg	0.84	0.84	0.00
11. Water	m3	2930.80	2989.2	0.83
12. Machinery	h	23	207.45	0.05
Total energy input	MJ/ha	74230.38	358261.63	100
Total energy output	MJ/ha	187718.1	150174.50	100

The highest share in energy consumption is 55.4% accounted for by fuel. Fuel in the study site is mainly used for the heating of the greenhouses. The second highest share in energy consumption is for electricity that accounts for 22.8% of energy consumption. Following fuel and electricity, chemical fertilizers are responsible for 8.4% of energy consumption and, as expected, nitrogen fertilizer has a greater share in total input energy than other fertilizers so that it accounts for 4.89% of total energy consumption. Among all inputs, seed has the lowest share in total energy consumption. In addition to local climate that is cold and dry, high rate of fuel consumption is associated with the use of fuel to stabilize the greenhouse temperature to hinder chilling and damping-off, especially at nights. The greenhouse skeletons that are not standard are another reason responsible for high fuel consumption rate. However, it should be noted that because of the cold climate of the region, greenhouse cucumbers are not planted in cold seasons because it is uneconomical due to high fuel consumption and low energy efficiency. So, summer planting usually commences in February 2016, in which case the fuel consumption rate declines with the coming of spring and the gradual warming of the weather. A part of electricity is consumed by the furnaces of the heating systems and the other part is used by ventilation systems, cooling systems, drip irrigation, water solvents, and for illumination. Nonetheless, less artificial light is used in greenhouses of Iran as Iran is located in a zone with longer days so that greenhouses enjoy an adequate amount of sunlight. The high consumption rate of nitrogen fertilizer is associated with the nature of cucumber because this crop requires a great deal of nitrogen for its vegetative growth and productivity.

Many researchers have reported the high share of fuel, electricity, and chemical fertilizer in total input energy. For example, in Heidari and Omid (2010) that studied energy consumption and economically analyzed cucumber and tomato greenhouses of Tehran Province, Iran, the input energy was mainly accounted for by diesel and chemical fertilizers [13]. These results are consistent with the findings other researchers [24,25]. Table 3 shows the indices of energy ratio, energy productivity, energy intensity, and net energy gain for greenhouse cucumber production. Similar results have been reported by multiple researchers. In their study on input and output energies of cucumber greenhouses in Jiroft County, Boland Nazaret al. (2015) estimated energy ratio at 0.52 [12].

TABLE 3. The values of energy consumption indices for cucumber greenhouses

Energy indices	Unit	Value
Energy ratio	-	0.42
Energy productivity	kg/MJ	0.52
Energy intensity	MJ/kg	1.91
Net energy	MJ/ha	-28091761.61

To better understand the results, total consumed energies are once divided into renewable and non-renewable energies and the other time into direct and indirect energies. According to the results, much more direct energy (energy content of irrigation water, fuel, electricity, labor, etc.) is used in the studied crop production than the indirect energy. This is related to the high consumption rate of the direct energy of fuel and electricity that have the greatest share in inputs. This result is in agreement with other researches [11]. They found that direct energies accounted for 86% of total energy consumption in cucumber greenhouses of Tehran while the rest (14 percent) was devoted to indirect energies. According to Table 4, non-renewable energies are consumed to a much greater extent than renewable energies. It can be observed that 88% of energy consumption for greenhouse cucumber production is accounted for by non-renewable energies whereas 12% is related to renewable energies. Similar results have been seen in most crops so that the share of nonrenewable energies is much greater than that of renewable energies that reported by other researches [16; 30]. This calls for more attention to our responsibility to safeguard the right of the next generations to use energy resources.

Table 4. The forms of energy consumption in cucumber greenhouses

Energy forms	Quantity (MJ/ha)	Percent (%)
Renewable	5927300.14	0.12
Non-renewable	42438020.02	0.88
Direct	43315148.76	0.90
Indirect	5050171.39	0.10

3.1.ANNMODELS

MLP model was implemented by the learning method of back-propagation of error using the Levenberg-Marquardt algorithm. To find out the best structure, different structures with one or two hidden layers and various neurons in the hidden layer were trained and validated. Since the performance of the network is dictated by two main features, i.e. the number of hidden layers and the number of neurons in the hidden layer, numerous trial-and-error tests on different structure led to the result that the network with one single hidden layer and different neurons in that hidden layer had the best structure. The rate of inputs, including of water, electricity, fuel, labor, machinery, chemical fertilizers (nitrogen, potash, and phosphate), micronutrients, manure, herbicides, and seeds, were included as the model input and energy consumption was regarded as the model output as depicted in Figure 1. Different topologies to forecast the energy consumption were tested according to Table 5. Table 4 shows the topology with the 12-14-1 structure exhibited the best performance. Table 5 shows that the R^2 value is 0.870 for energy productivity of greenhouse cucumber production, implying that the MLP model can forecast the energy consumption of cucumber production with a high accuracy. Khoshnevisan *et al*. (2013b) modeled the energy consumption and GHG emission during wheat production in Isfahan Province and reported that the neural network model composed of 11 input parameters, 2 hidden layers, and 5 neurons could simultaneously forecast two output parameters, including of output energy and GHG emission rate with a very high precision and low error [17].

Table 5. The results of modeling by the MLP artificial neural network

No. of neurons in the hidden layer	RMSE			R2		
	Testing	Training	Total	Testing	Training	Total
10	0.089	0.088	0.0885	0.873	0.842	0.870
12	0.1004	0.115	0.1121	0.788	0.804	0.789
14	0.093	0.086	0.089	0876	0.851	0.087
16	0.118	0.110	0.1129	0.794	0.711	0.776
18	0.117	0.117	0.108	0.821	0.833	0.804

A nonlinear Gaussian function was employed by RBF model in ANN. Cucumber inputs were included as the input data, and cucumber yield was included as the system output. In the context of this model, five structures were assessed as presented in Table 5. The best structure to forecast the cucumber yield was found to be 1-22-12-12 topology. According to Table 6, the RBF model can forecast the energy productivity of cucumber with 95.5% precision Faizollahzadeh Ardabili et al. (2016) examined the control and simulation systems of air conditioning system using the ANFIS and RBF models of neural networks [26]. Output temperature and moisture were estimated by the RBF model with R^2 of 0.924 and 0.852 and by AFNIS with R^2 of 0.832 and 0.773, respectively. The results showed the RBF model outperformed the ANFIS model.

Table 6. The results of modeling by the RBF artificial neural network

No. of neurons in the hidden layer	RMSE			R2		
	Testing	Training	Total	Testing	Training	Total
16	0.089	0.077	0.081	0.906	0.848	0.892
18	0.087	0.072	0.086	0.918	0.859	0.903
20	0.080	0.07	0.080	0.923	0.905	0.919
22	0.059	0.00	0.053	0.961	0.936	0.955
25	0.059	0.050	0.053	0.961	0.936	0.955

3.2. ANFIS

In addition to MLP and RBF, ANFIS was employed to model the energy consumption of cucumber greenhouses. ANFIS is a mixture of neural networks and fuzzy systems that is used as a robust modeling tool. To gain the best model by ANFIS, changes were made in different parameters including of the

number and type of input and output membership function, optimization methods, and the number of epochs. A necessary change to obtain the best ANFIS structure was the number of membership functions. The number of membership functions shows the total number of parameters in the ANFIS networks that should be smaller than the number of training data pairs [27]. Overall, this was done with a Gaussian function and three membership functions in the hidden layer in the linear mode. Finally, RMSE was 0.080, and R^2 was 0.892. These results are in agreement with other studies. In their research on estimating the environmental impacts of greenhouse cucumber and tomato production, Khoshnevisan et al. (2014) estimated R^2 and RMSE to estimate the global warming potential index at 0.998 and 0.015 for cucumber and 0.997 and 0.01 for tomato, respectively [27]. Naderloo et al. (2012) reported that RMSE and R^2 were 0.013 and 0.996 in their attempt to forecast the wheat yield, respectively [5].

3.3. MULTIPLE REGRESSIONS

We used multiple regressions by the SMLR method in our modeling, in which the independent variables were the cucumber production inputs including of seed, water, herbicide, fertilizers (nitrogen, potash, and phosphate), micronutrients, manure, labor, electricity, and machinery, and the dependent variable was the output, i.e. greenhouse cucumber yield.

The results showed that R2 and RMSE were 0.397 and 0.157, respectively. This means that the employed linear regression model had low accuracy and failed to forecast the energy consumption of greenhouse cucumber production well.

3.4. ANN, ANFIS, and REGRESSION

Table 7 shows that among the models used to forecast energy consumption of greenhouse cucumber production, R2 was 0.955 for the RBF model, showing higher accuracy than ANFIS and regression. Also, ANFIS outperformed multiple regressions.

TABLE 7. The performance of different methods in forecasting energy consumption of greenhouse cucumber production

Modeling methods	RMSE	R^2
RBF artificial neural network	0.053	0.955
ANFIS	0.08	0.892
EMRL multivariate regression model	0.631	0.397

Although the AFNIS model has fuzzy rules, the capability of ANNs in discovering the nonlinear relationships among the input data was considerable and they need less calculation effort than the conventional models like regression. These models are mainly characterized by high processing speed, the capability of model learning by pattern determination method, and its flexibility against unwanted data. By comparing the results of ANN, ANFIS, and regression models, we draw the conclusion that ANNs can estimate output values with higher accuracy and lower error. Our results are consistent with similar studies [28; 23 and 29]. In a study to compare the accuracy of linear regression, MLP, RBF, and ANFIS to predict output energies of broiler production, Amid and Mesri Gundoshmian (2016) showed that RBF and ANFIS were more accurate than other methods. In other study, Khoshnevisan et al. (2013) found that the ANFIS models outperformed the ANN method in estimating output energy because they use fuzzy rules [23]. Also, Mehrjordi et al. (2013) used neuro-fuzzy, ANN, genetic algorithm, and multivariate regression models [28]. The assessments showed that the neuro-fuzzy model outperformed all other models in the prediction of forecasting soil features. Wali et al. (2011) reported that ANN gave better results than the multivariate regression [29].

4. CONCLUSION

The results showed that among the inputs used to produce greenhouse cucumber in East Azerbaijan Province, fuel had the highest share of 55.47% in input energy followed by electricity with a 22.75% share, fertilizers with a 12.18% share, and labor with a 7.58% share. In modeling by MLP and RBF ANNs to forecast energy consumption of greenhouse cucumber production, R^2 was 0.955 for RBF showing higher accuracy than MLP. Among ANFIS, RBF, and multiple regressions, RBF had an R^2 of 0.955 and showed the highest accuracy for prediction of energy consumption in greenhouses.

CONFLICT OF INTEREST

The authors declare no conflict of interest

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