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Developing an Artificial Neural Networks Model for Predicting Output Energy and GHG Emission of Strawberry Production

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Abstract In this study an artificial neural network was developed to predict output the energy and GHG emission of open field (OF) and greenhouse (G) strawberry production system. Data were randomly collected from OFs and Gs in Guilan province of Iran. For both systems the best models included an input layer, two hidden layers with hyperbolic tangent algorithm and an output layer with linear hyperbolic tangent algorithm. The structures of 11-6-10-2 and 13-7-6-2 were selected as the best topologies for OF and G production systems, respectively. These topologies had the least root mean square errors (RMSE) and mean absolute errors (MAE).

Keywords Energy, Strawberry, Artificial Neural Networks, GHG Emission.

1 Introduction

Strawberry belongs to the family *Rosaceae*, genus *Fragaria*, and is among the most widely consumed fruits throughout the world. Currently, the United States of America, Spain, Turkey, the Russian Federation, and the Republic of Korea are the main strawberry producer countries [1]. Open field (OF) strawberry production as a conventional method has been used to supply the domestic demand for this crop in Iran. The high demand for fresh an off-season strawberry along with its gross value of production and nutrient value encourages greenhouse holders to grow widely this crop in their greenhouses. In the period of 2002 to 2007, greenhouse areas of Iran had expended from 3380 ha to 6630 ha including an increasing rate of 96%. The shares of greenhouse crops production were as follows: vegetables 59.3%, flowers 39.81%, fruits 0.54% and mushroom 0.35% [2]. Greenhouses are considered as intensive farming from productive point of view; however they are the most important energy consumer in the agricultural sector.

Energy is a fundamental component in the process of economic development, as it provides imperative services that maintain economic activities and the quality of human life.

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Thus, shortages of energy are a serious constraint on the development of low income countries [3]. Energy, economics, and the environment are mutually dependent. Moreover, there is a close relationship between agriculture and energy; agriculture itself is an energy user and energy supplier in the form of bio-energy [4]. Energy input-output analyses are usually applied to investigate the energy use efficiency and determine the environmental facets of inefficient energy consumption. Several studies have been conducted on energy use in OF and G productions [4-7].

Artificial neural networks (ANN) have been widely used in different fields of agriculture like economic, energy and environmental modeling as well as to extend the field of statistical methods, in the last few decades. The advantage of ANNs over statistical methods is reported in Zhang, Eddy Patuwo and Y. Hu [8]. The main reason that ANN applications have received considerable attention is that the methodology is comparable to statistical modeling and ANNs could be faced as complementary effort (without the restrictive assumption of a particular statistical model) or an alternative approach to fitting non-linear data [9]. Of statistical models, ANN, which relates input-output variables without explicit information on the processes causing the response, has been used for describing the complex non-linear relationships across many scientific studies [10].

In recent years, several studies have been carried out by application of ANNs. Rahman and Bala [11] employed ANNs to estimate jute production in Bangladesh. In this study an ANN model with six input variables including Julian day, solar radiation, maximum temperature, minimum temperature, rainfall, and type of biomass was applied to predict the desired variable (plant dry matter). Pahlavan, Omid and Akram [12] developed a network for the prediction of greenhouse basil production. Safa and Samarasinghe [13] employed ANNs for determination and modeling of energy consumption in wheat production. They compared ANNs with Multiple Linear Regression and found that artificial neural networks can predict energy consumption better than regression models.

Considering the importance of energy consumption and its environmental consequences, the main objective of this study was to develop ANN models to predict output energy and GHG emission of strawberry production on the basis of energy inputs.

2 Materials and methods

2.1 Data collection and processing

The present study was carried out in the province of Guilan in Iran because both strawberry production systems – Open field and greenhouse – are widely used simultaneously. Data were collected from rural areas of Rasht (The capital of Guilan province; a province in the north of Iran next to the Caspian lake) in 2011/2012 production year. The sample size was determined using the Cochran technique [4]. Based on this sampling method, 70 open field owners and 33 greenhouse holders were chosen and inquired using face-to-face questionnaire method.

Energy inputs for G production included human labor, chemical fertilizers, farmyard manure (FYM), diesel fuel, electricity, natural gas, biocides, machinery and water for irrigation while for OF production it encompassed Labor, fertilizers, FYM, diesel fuel, electricity, Biocides, machinery and irrigation water. For both systems, the amount of strawberry produced was considered as output energy. Energy equivalents of inputs and outputs (Table 1) were exercised to assess the total energy inputs and outputs.

The amount of rainfall in the studied region is good, so rainfall can provide some parts of plants' water need in OF production and the rest is provided by agricultural wells. Water for irrigation was extracted from agricultural well by electric pumps. Energy needed for pumping water was calculated as Eq. 1 [14]:

$$\mathrm{DE} = \frac{\gamma\, \mathrm{g}\, \mathrm{H}\, \mathrm{Q}}{\varepsilon_{\mathrm{p}} \varepsilon_{q}} \tag{1}$$

where 'DE' presents direct energy (J/ha), 'g' is acceleration due to gravity (ms^{-2}), 'H' is total dynamic head (m), 'Q' is volume of required water for one cultivating season (m^3 ha^{-1}), 'γ' is density of water (kg m^{-3}), 'ε_p' is pump efficiency (70-90%) and 'ε_q' is total power conversion efficiency (18-20%) [3].

Machinery Energy was calculated by the following formula [15]:

$$ME = \frac{ELG}{TC_a} \tag{2}$$

where 'ME' is the machine energy (MJ ha^{-1}), 'G' the weight of machine (kg), 'E' the production energy of machine (MJ kg^{-1} yr^{-1}) that is shown in Table 1, 'L' the useful life of machine (year), 'T' the economic life of machinery (h) and 'C_a' the effective field capacity (ha h^{-1}).

Table 1 Energy coefficients of different inputs and output used

Inputs	Unit	Energy coefficients (MJ $unit^{-1}$)	Reference
A. Inputs			
1. Machinery			
Tractor and self-propelled	kg yr[a]	9-10	[4]
Stationary equipment	kg yr[a]	8-10	[4]
Implement and machinery	kg yr[a]	6-8	[4]
2. Human labor	h	1.96	[2]
3. Natural gas	m^3	49.5	[14]
4. Diesel fuel	L	47.8	[14]
5. Biocide			
Herbicide	kg	85	[5]
Fungicide	kg	295	[5]
Insecticide	kg	115	[5]
6. Fertilizers			
Nitrogen (N)	kg	66.14	[1]
Phosphate (P_2O_5)	kg	12.44	[1]
Potassium (K_2O)	kg	11.15	[1]
Micro	kg	120	[1]
9. FYM	kg	0.3	[4]
10. Water for irrigation	m^3	1.02	[2]
11. Electricity	kWh	12	[14]
B. Output			
1. Strawberry	kg	0.8	[1]

Production, formulation, storage, distribution of agricultural inputs and their applications with agricultural machinery lead to the combustion of fossil fuel, and use of energy from alternate sources which emits CO_2 and other greenhouse gases (GHGs) into the atmosphere [16]. To quantify the GHG emission of strawberry production, carbon emission coefficients of agricultural inputs were applied. Table 2 summarized GHG emission equivalents. GHG emission was worked out by multiplying the input application rate (diesel fuel, chemical fertilizers, machinery, pesticides, electricity and natural gas) by its corresponding emission coefficient. By calculation of carbon emission equivalent of each energy input, we can make a comparison between two various production systems regarding the environmental problems.

Table 2 Greenhouse gas (GHG) emission coefficients of agricultural inputs

Inputs	Unit	GHG coefficients [a]	Reference
Machinery	MJ	0.071	[5]
Diesel fuel	L	2.76	[5]
Chemical fertilizers			
(a) Nitrogen (N)	kg	1.3	[16]
(b) Phosphate (P_2O_5)	kg	0.2	[16]
(c) Potassium (K_2O)	kg	0.2	[16]
Biocide			
(a) Herbicide	kg	6.3	[16]
(b) Insecticide	kg	5.1	[16]
(c) Fungicide	kg	3.9	[16]
Natural gas	m^3	0.85	[16]
Electricity [b]	kWh	0.608	[5]

2.2 Selecting inputs for the ANN model and model development

To model the output energy and GHG emission, input energies (human labor, chemical fertilizers, FYM, diesel fuel, water for irrigation, electricity, natural gas, biocides and machinery) along with the farm sizes were regarded as the inputs of the model and strawberry energy and GHG emission were chosen as outputs of the model.

The artificial neural networks are basically computational models, which simulate the function biological networks, composed of neurons [17]. In the feed forward neural networks, inputs enter to the first layer without performing any computations while in a hidden layer they are firstly computed and then pass through an activation function – linear or nonlinear – as following [18]:

$$z_j = v_j\left(\sum_{i=1}^{p} w_{ij}^h x_i + \rho_j\right), \quad j=1,2,\ldots,m. \tag{3}$$

where 'v_j' is the activation function in the hidden layer, 'p' presents input number, 'h' states the symbol of hidden layer, and 'ρ' presents bias term.

A back-propagating neural network (BPNN), which has been identified as the most common ANN model, was used to develop prediction models. BPNN structures usually consist of a layer of input neurons, a layer of output neurons and one or more hidden layers (

Fig. 1). The model can be written mathematically as [12]:

$$\mathrm{y_t} = \alpha_0 + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-i} + \beta_{0j}\right) + \varepsilon_t \qquad [\mathrm{i}=1,\ldots,\mathrm{m\ and\ j}=1,\ldots,\mathrm{n}] \tag{4}$$

where 'm' is the number of input nodes, 'n' is the number of hidden nodes, 'α_j' denotes the vector of weights from the hidden to output nodes and 'β_{ij}' denotes the weights from the input to hidden nodes. 'α_0' and 'β_{0j}' represent weights of arcs leading from the bias terms which have values always equal to 1 and 'f' is a sigmoid transfer function.

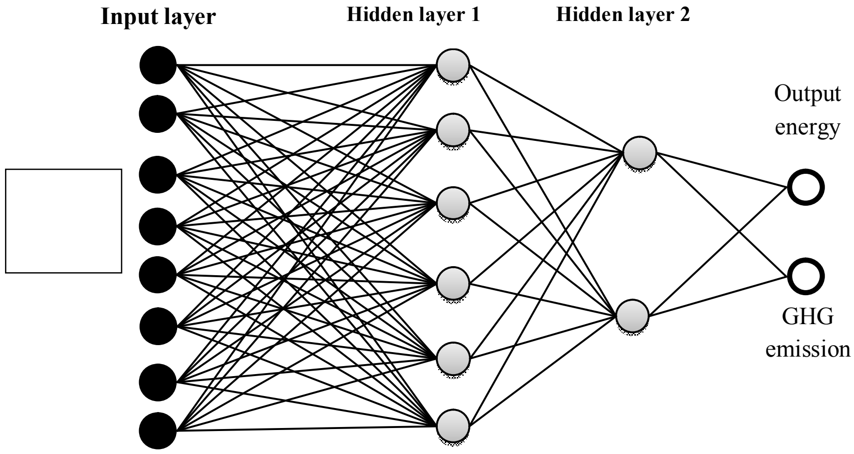

Fig. 1 A BPNN structure with two hidden layers

The performance of the network can be evaluated by comparing the error obtained from the converged neural network runs and the measured data. The error function can be expressed as [19]:

$$E = \frac{1}{p}\sum_{p}\sum_{k}\left(t_{pk} - z_{pk}\right)^2 \tag{5}$$

where 'p' is the index of the p training pairs of vectors, 'k' is the index of element in the output vector, 't_{pk}' is the kth element of the pth desired pattern vector, and 'z_{pk}' is the kth element of the output vector when pattern p is presented as input to the network.

Some criteria were selected to evaluate the performance of the model. The coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE) were used for characterizing the network performance. R^2, RMSE and MAE are defined as following [12]:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2}\right) \tag{6}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{i}^{n}\left(t_i - z_i\right)^2} \tag{7}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|(t_i - z_i)\right| \tag{8}$$

where 'n' is the number of the points in the data set, and 't' and 'z' are actual output and predicted output sets, respectively. The BPNN giving the minimum RMSE, MAE and the best R^2 was regarded as the best topology. NeuroSolutions 5.07 package [20] was applied to develop BPNN.

3 Results and Discussions

3.1 Analysis of Input-output energy for strawberry production

The amount of input energies from different sources and output energy as well as their energy equivalents in OF production are presented in Table 3. The results showed that the total input energy was 35092.4 MJ ha^{-1}; while, the total output energy was computed as 10405.9 MJ ha^{-1}. Based on the results, 5748 MJ ha^{-1} labor energy was used in various operations. It was mainly applied in harvesting operations (40%), irrigation (28%) and weeding (25%). The average amount of chemicals used for OF strawberry production was 33.3 kg which seems was too high due to its negative environmental and human health consequences. No studies have been carried out on input-output energy analysis for OF strawberry production, so, the results were compared with other crops. In a study on energy use pattern of some field crops in Turkey carried out by Canakci, Topakci, Akinci and Ozmerzi [21], 18680.8, 34891.2, 25584.6 and 9725.6 MJ ha^{-1} were reported as total input energy for wheat, cotton, maize and sesame productions, respectively. Mousavi-Avval, Rafiee, Jafari and Mohammadi [4] on their study on functional relationship between energy inputs and yield value of soybean production in Iran showed that the total input and output energies were calculated as 35372.23 and 80828.75 MJ ha^{-1}, respectively.

Table 3 Amounts of inputs, output and their energy equivalents in open field strawberry production

input	Unit	Quantity (unit per ha)	TEE[a] (MJ ha^{-1})	SD[b]
A. Input				
1. Human labor	h	2932.6	5748	1543.6
2. Chemical fertilizer				
a. N	kg	216.4	14313.3	4596.0
b. P_2O_5	kg	200	2488.1	699.3
c. K_2O	kg	243.9	2719.8	989.2
3. FYM	kg	5410.2	1623.1	521.2
4. Biocides	kg	33.3	3166.9	359.1
5. Machinery	kg	5708.8	1121.8	703.9
6. Water for irrigation	m^3	991.5	1011.3	56.8
7. Diesel fuel	L	28.3	1354.4	820.5
8. Electricity	kWh	129.6	1545.6	86.8
Total input energy			35092.4	5814.6
B. Output				
Strawberry	kg	5476.8	10405.9	2303.9

[a] Total energy equivalent
[b] Indicates standard deviation for energy inputs (MJ ha^{-1})

The contribution of different input energies used in OF strawberry production is illustrated in Fig. 2. As can be seen the highest share in total input energy was consumed by chemical fertilizers (56%), followed by human labor (16%) and biocide (9%). The high consumption of chemical fertilizer energy demonstrated the inappropriate fertilizer usage in the studied area.

Applying soil analysis to specify the soil fertilizer needs and application of composts can decrease the amount of fertilizer energy without any negative effects on yield.

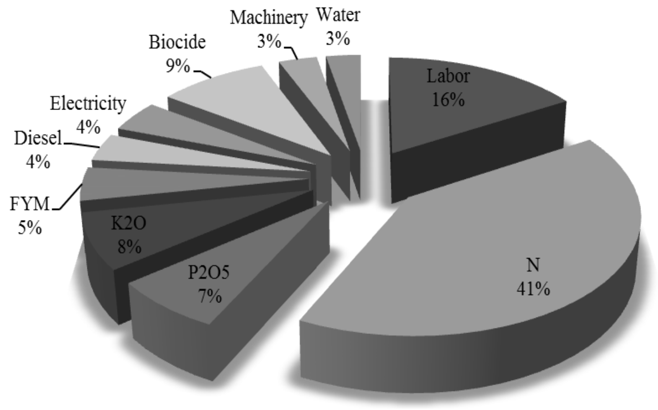

Fig. 2 Contribution of different input energies for open field strawberry production

Table 4 summarizes the energy use pattern for greenhouse strawberry production in the studied region. As can be seen from the standard deviations in the last column of Table 4, inhomogeneity among the greenhouses is conspicuous. Inhomogeneity was due to different technologies, various practices and the different technical knowledge of greenhouse holders.

The average of labor, chemical fertilizer, FYM, biocides, machinery, water for irrigation, diesel, electricity and natural gas energies were estimated as 25134.3, 104067.8, 19454.5, 6281.7, 1154.5, 24353.3, 12785.3, 372068.4 and 792392.9 MJ ha^{-1}, respectively. The total input energy and output energy for greenhouse strawberry production were calculated as 1357692.6 and 137772.4 MJ ha^{-1}. Several studies have been conducted on input-output energy for greenhouse crops. The total input energy for greenhouse strawberry, cucumber, basil was reported as 805376.3 [1], 1168023.29 [22] and 14308998 MJ ha^{-1} [12], respectively.

Table 4 Amounts of inputs, output and their energy equivalents in greenhouse strawberry production

input	Unit	Quantity (unit ha^{-1})	TEE[a] (MJ ha^{-1})	SD[b]
A. Input				
1. Human labor	h	12823.6	25134.3	6143.8
2. Chemical fertilizer				
a. N	kg	675.2	44654.5	13494.1
b. P_2O_5	kg	2025.5	25196.7	7614.2
c. K_2O	kg	1050	11707.5	3476.0
d. Micro	kg	187.6	22509.1	7840.5
3. FYM	kg	64848.5	19454.5	6235.4
4. Biocides	kg	39.7	6281.7	529.2
5. Machinery	kg	6581.8	1154.5	433.9
6. Water for irrigation	m^3	23875.8	24353.3	17437.0

input	Unit	Quantity (unit ha^{-1})	TEE[a] (MJ ha^{-1})	SD[b]
7. Diesel fuel	L	267.5	12785.3	6016.7
8. Electricity	kWh	31187.6	372068.4	155584.0
9. Natural gas	m^3	16007.9	792392.9	1065148.6
Total input energy	MJ/ha		1357692.6	1060928.6
B. Output				
Strawberry	MJ/ha	72511.8	137772.4	28608.6

[a] Total energy equivalent
[b] Indicates standard deviation for energy inputs (MJ ha^{-1})

As it is illustrated in
Fig. 3 Natural gas with a portion of 58.3% was the most energy consumer, and it was followed by electricity (27.4%). The majority of natural gas and electricity were used for heaters and drop irrigation systems. Heidari, Omid and Mohammadi [22] in their studies on measuring productive efficiency of greenhouse cucumber showed that from the total input energy the share of diesel fuel and electricity, respectively by 68% and 18% were the highest. They mentioned that the diesel fuel was mostly used for heating systems. In another study which was conducted by Omid, Ghojabeige, Delshad and Ahmadi [2], the same results were obtained.

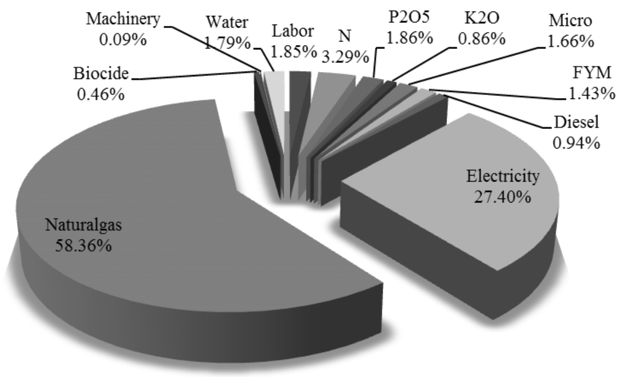

Fig. 3 Contribution of different input energies for greenhouse strawberry production

3.2 GHG emission

The amounts of GHG emission for two production systems are demonstrated in Table 5. The total GHG emission for OF and greenhouse production were 803.4 and 35083.5 kg CO_2 eq. ha^{-1}, respectively. The Electricity with the amount of 18962.1 kg CO_2 eq. ha^{-1} played the most important role within the G production system while chemical fertilizer with the amount of 370.1 kg CO_2 eq. ha^{-1} was regarded as the most significant factor within the OF production system. No study was carried out on GHG emission of strawberry production, so we compared our results with the results of other crops. Pishgar-Komleh, Ghahderijani and Sefeedpari [5] reported that the total value of GHG emission of potato production was calculated as 992.88 kg CO_{2eq} ha^{-1}.

Table 5 GHG emission of strawberry production under two different systems (kg CO_2 eq. ha^{-1})

Item	Diesel	Fertilizer	Machinery	Electricity	Biocides	Natural gas	Total
Open field	78.2	370.1	79.6	78.8	196.7	-	803.4
Greenhouse	738.2	1492.8	82.0	18962.1	201.7	13606.7	35083.5

3.3 ANN models: evaluation and error analysis

To find the best topology for each production system several BPNN were designed, trained and generalized. No transfer function for the first layer was used but for the hidden layers and the output layer the sigmoid, hyperbolic tangent, logsig and different linear transfer functions were examined in each hidden layer. Data were randomly grouped into 3 sets; training set (60%), cross validation set (25%) and testing set (15%).

For OF production, the best model consisted of an input layer with eleven input variables, two hidden layers with six and ten neurons in first and second hidden layer, respectively along with an output layer with two variables (11-6-10-2 structure). The hyperbolic tangent was employed in the hidden layers, and linear hyperbolic tangent was applied in the output layer. This topology had the highest R^2 and the lowest RMSE and MAE. Calculated performance criteria for these values are given in Table 6.

Table 6 The best result of different arrangement of models

Item	Output energy			GHG emission		
	RMSE	MAE	R^2	RMSE	MAE	R^2
Open field production	0.127	0.103	0.93	0.047	0.032	0.99
Greenhouse production	0.236	0.211	0.93	0.183	0.16	0.97

Based on the results, the best model for G production included an input layer with thirteen variables, two hidden layer with seven and six neurons, respectively, as well as an output layer with two variables (13-7-6-2 structure). Pahlavan, Omid and Akram [12] reported that a model consisted of an input layer with seven neurons, two hidden layers with 20 neurons in each one and one neuron in the output layer was the best one for predicting basil production in Esfahan province of Iran. Safa and Samarasinghe [13] developed an ANN model based on a modular neural network with two hidden layers that can predict energy consumption based on farm conditions (size of crop area), social factors (farmers' education level), and energy inputs (N and P use, and irrigation frequency). Their result showed the ability of ANN model to predict energy consumption in wheat production using heterogeneous data. Rahman and Bala [11] showed that a model in compassed of an input layer with six neurons, two hidden layers with 9 and 5 neurons and one neuron in the output layer was the best model for predicting jute production in Bangladesh.

3.4 Sensitivity analysis

The influence of input parameters on the outputs was investigated by sensitivity analysis. In fact the robustness of the model was determined by examining and making a comparison between the outputs produced during the validation stage and the calculated values [12]. The sensitivity factors for input parameters are presented in Fig.4 and Table 7.

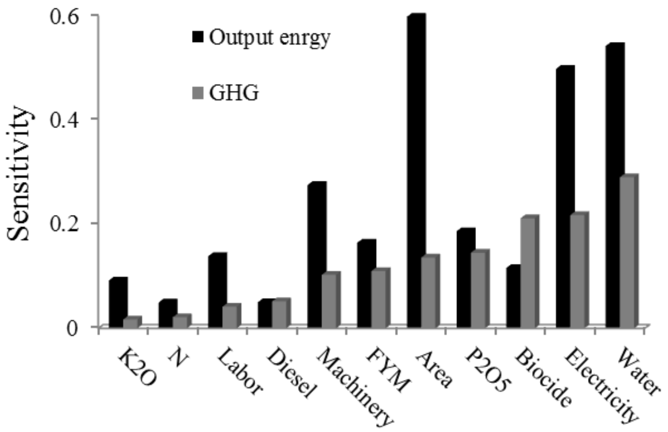

Fig.4 Sensitivity analysis of various input energies on open field strawberry output energy and GHG emission

As can be seen in

Fig.4, in OF production, farm size had the highest sensitivity factor for output energy, followed by water and electricity while water, electricity and biocide had the most important role on GHG emission. Also, the sensitivity of nitrogen and diesel were relatively low for output energy and GHG emission had the least sensitivity to Potassium and nitrogen.

Based on the results of greenhouse production which are illustrated in Table 7, Output energy was highly sensitive to Area, labor and diesel, respectively, while its sensitivity to micro elements, nitrogen, phosphorous and electricity was low. As it is demonstrated the GHG emission was sensitive to natural gas and electricity.

Table 7 Sensitivity analysis results for greenhouse strawberry input energies

Item	Output energy	GHG emission
Area	0.57	0.09
FYM	0.19	0.10
N	0.03	0.20
P2O5	0.03	0.08
K2O	0.10	0.05
Micro	0.01	0.11
Biocide	0.19	0.01
NG	0.04	0.41
Labor	0.24	0.04
Water	0.13	0.05
Electricity	0.03	0.37
Diesel	0.21	0.06
Machinery	0.07	0.05

4 Conclusions

The main objective of this study was to model output energy and GHG emission of OF and G strawberry production in the province of Guilan, Iran. In addition, the energy use pattern of these production systems was compared. The results revealed that the total input and output energies in OF strawberry production were 35092.4 and 10405.9 MJ ha^{-1}, and simultaneously the total GHG emission was 803.4 kg CO_2 eq. ha^{-1}. Based on the results, chemical fertilizer was the most influential factor in energy consumption and GHG emission. For G strawberry production the following results were concluded. The total input energy was 1357692.6 MJ ha^{-1}, and its related GHG emission was calculated as 35083.5 kg CO_2 eq. ha^{-1}, and it was mainly dependent on non-renewable energy sources such as natural gas and electricity. Moreover, the total output energy was computed as 137772.4 MJ ha^{-1}.

For OF production, the ANN model with 11-6-10-2 structure was the best one for forecasting the output energy and GHG emission. For the best topology RMSEs were 0.127 and 0.047, MAEs were 0.103 and .032 for output energy and GHG emission, respectively. The developed model for G production with 13-7-6-2 structure had the least RMSEs and MAEs. The RMSEs were 0.236 and 0.183, MAEs were 0.211 and 0.16 for output energy and GHG emission, respectively.

Acknowledgements

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