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Applying artificial neural networks and multi-objective genetic algorithm to modeling and optimization of energy inputs and greenhouse gas emissions for peanut production

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Abstract

This study was conducted in order to model energy consumption and greenhouse gas emissions for peanut production in Guilan province of Iran using artificial neural network (ANN). Also, the multi-objective genetic algorithm was used for optimization of energy inputs and GHG emissions in the region. Data were randomly collected from 120 farms in Astaneh Ashrafiyeh city with face to face questionnaire method. The results illustrated that the total energy consumption and the average yield were calculated as 19248.04 MJ ha^{-1} and 3488.39 kg ha^{-1}, respectively. Moreover, the results showed that the share of chemical fertilizers (mainly nitrogen) and diesel fuel energy to the total energy input were the highest. Also, the energy used efficiency ratio calculated as 4.53. The results of GHG emissions analysis showed the total GHG emissions were 571.18 kgCO$_{2eq.}$ ha^{-1} and the diesel fuel has the main reasonable of GHG emissions in peanut production. In this study, several direct and indirect factors have been identified to create a model based on ANN to predict energy use and GHG emissions in peanut production. The ANN model with 9-22-2 structure was capable of predicting the peanut yield and GHG emissions. Moreover, the results of the best topology showed that R^2 was 0.994 and 0.999, RMSE was 0.076 and 0.003 and MAPE was 0.174 and 0.009 for peanut yield and GHG emissions, respectively. The results of optimization indicated the total energy consumption and GHG emissions generation was calculated about 6888 MJ ha^{-1} and 159.08 kgCO$_{2eq.}$ ha^{-1}, respectively. The total GHG emissions reduction was found to be 412.09 kgCO$_{2eq.}$ ha^{-1} in optimal generation toward present farms.

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Introduction

Peanut production is very important for Iran in terms of both export and domestic consumption. In Guilan province of Iran peanut is established preferably in spring (April and May) and it is harvested once a year (in September and October). Guilan province is one of the major peanut producing provinces in Iran. In Guilan, it is mostly planted in Astaneh Ashrafiyeh city and also on Kiyashahr port (Anon, 2012). Wider use of renewable energy sources, increase in energy supply and efficiency of use can make a valuable contribution to meet sustainable energy development targets (Streimikiene *et al.,* 2007). Agriculture itself is an energy user and energy supplier in the form of bio-energy (Alam *et al.,* 2005). Energy input-output analysis is usually used to evaluate the efficiency and environmental impacts of production systems. Efficient use of energy in agriculture will minimize environmental problems, prevent destruction of natural resources, and promote sustainable agriculture as an economical production system (Erdal *et al.,* 2007). Historically, the efficient use of energy in agriculture did not have a high priority but recently the use of energy resources has increased markedly with advancement in the technology and general agricultural developments (Chaudhary *et al.,* 2009). Energy consumption by the agriculture sectors can be broadly categorized into direct and indirect energy use. Agriculture directly uses energy as fuel or electricity to operate machinery and equipment, to heat or cool buildings and to light the farm and indirectly in the chemical fertilizers, seed production, machinery and biocides produced off the farm (Ozkan *et al.,* 2004). The greenhouse effect is a natural process by which some of the radiant heat from the Sun is captured in the lower atmosphere of the Earth, thus maintaining the temperature of the Earth's surface. The gases that help capture the heat, called "greenhouse gas (GHG)" such as CO_2. The main reason for GHG emissions in agriculture is CO_2 emissions from inputs. Artificial neural networks (ANNs) have used for prediction, solving problems, sensitivity analysis and classification, in the field of energy. The genetic algorithm (GA) is a global optimization method based on the principle of survival of the fittest—Darwin's hypothesis of evolution (Bala and Siddique, 2009). The basic principles of the GA are attributed to Holland (1975) and further developed for engineering applications by Goldberg (1989) and Michalewicz (1996). Considerable researches have been conducted on energy use, GHG emissions and optimization of energy in agriculture. Unakitan *et al.* (2010) studied the energy inputs and economic analysis in canola production for reducing the energy consumption of food production in Turkey. The results showed the difference between average input and output energy is 67259.36 (MJ ha^{-1}). In another study, Rahman and Bala (2010) estimated jute production in Bangladesh using ANNs. In their study, ANN model with six input variables was applied to predict the desired variable (plant dry matter). Also, Ramedani *et al.* (2011) determined the value of energy consumption for producing 1 kg soybean and determination of energy indices in cultivating soybean for Golestan province of Iran. Mobtaker *et al.* (2012a) modeled energy consumption for alfalfa production. Then, in another paper, they optimized energy inputs for this crop (Mobtaker *et al.,* 2012b). Safa and Samarasinghe (2011) determined modeling of energy consumption in wheat production using neural networks in Canterbury province, New Zealand. The results of this study showed the total energy consumption in wheat production was estimated at 22,566 MJ ha^{-1}. On average, fertilizers and electricity were used more than other energy sources, at around 10,654 (47%) and 4870 (22%) MJ ha^{-1}, respectively. Also, the results revealed the ANNs can predict energy consumption better than MLR (multiple linear regression). Khoshnevisan *et al.* (2013) employed ANNs for modeling of energy consumption and GHG emissions in wheat production in Esfahan Province of Iran. The results illustrated that averages of total input and output energy of wheat production were 80.1 and 38 GJ ha^{-1}, respectively. Moreover, the ANN model with 11-3-2 structure was the best one for predicting the wheat yield and GHG emissions. In another study, Hematian *et al.* (2013) investigated the energy consumption and optimization energy for sugar-beet production using genetic algorithm.

The main aim of this study was to predict peanut production yield and GHG emissions using ANNs. For this purpose, ANN models were developed and the quality parameters were applied to predict their accuracy of them. Moreover, the energy inputs and GHG emissions was to optimized for peanut production by multi-objective genetic algorithm and the effect of optimization were considered for potential of GHG emissions reduction.

Materials and methods

2.1. Data collection and processing

Data used in this study were collected from 120 peanut producers from Astaneh Ashrafiyeh region in Guilan province, Iran. In this study Guilan province was chosen as a representative of the Iranian peanut production enterprises. This province is located in the north of Iran, within 36° 34′ and 38° 27′ north latitude and 48° 53′ and 50° 34′ east longitude (Anon, 2012).

A face-to-face questionnaire was conducted in the production year 2012/2013. For estimating the required sample size, the simple random sampling method was used (Kizilaslan, 2009). Consequently calculated sample size in this study was 108, but it was considered to be 120 to ensure the accuracy.

The inputs used in the production of peanut were specified in order to calculate the energy equivalences in the study. Inputs in peanut production were consisted of: human labor, machinery, diesel fuel, chemical fertilizers, biocides and seed. The output was considered peanut yield. The energy equivalents, given in Table 1, were used to calculate the energy inputs. The inputs and output were calculated per hectare and then, these input and output data were multiplied by the coefficient of energy equivalent. Machinery Energy was calculated by the following formula (Hatirli *et al.,* 2005).

$$ME = \frac{ELG}{TC_a} \qquad (1)$$

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

The production energy of a machine ('*E*' in Eq. 1) is composed of the energy quantity of materials, energy required in the manufacturing process, the transportation of the machine to the consumer and the energy sequestered in repairs (Kitani, 1999; Khoshnevisan *et al.,* 2013).

Following the calculation of energy input and output values, the energy ratio (energy use efficiency), energy productivity, specific energy, net energy and energy intensiveness were calculated in various farm size groups. With respect to the farm sizes, samples were classified into three groups: small farms (<1 hectare), medium farms (between 1 and 3 hectare) and large farms (>3 hectare). The ANOVA test was utilized and the means were compared by the exercise of Duncan compare mean test (Mandal *et al.,* 2002; Mohammadi *et al.,* 2008; Banaeian *et al.,* 2010).

$$\text{Energy use efficiency} = \frac{\text{Energy Output (MJ ha}^{-1})}{\text{Energy Input (MJ ha}^{-1})} \qquad (2)$$

$$\text{Energy productivity} = \frac{\text{Peanut output (kg ha}^{-1})}{\text{Energy Input (MJ ha}^{-1})} \qquad (3)$$

$$\text{Specific energy} = \frac{\text{Energy output (MJ ha}^{-1})}{\text{Peanut output (kg ha}^{-1})} \qquad (4)$$

$$\text{Net energy} = \text{Energy Output (MJ ha}^{-1}) - \text{Energy Input (MJ ha}^{-1}) \qquad (5)$$

$$\text{Energy intensiveness} = \frac{\text{Energy input (MJ ha}^{-1})}{\text{Total production cost (\$ ha}^{-1})} \qquad (6)$$

The energy use efficiency is the ratio between the output products and the total sequestered energy in the production inputs. The energy use efficiency gives an indication of how much energy was produced per unit of input energy. The energy productivity provides quantitative data on how much peanut is obtained per unit of input energy. Net energy is defined as the difference between the gross energy output produced and the total energy used for obtaining it (Mobtaker *et al.,* 2010). Energy intensiveness is a measure of the amount of energy it takes to produce a dollar's worth of economic output, or conversely the amount of economic output that can be generated by one standardized unit of energy.

The amounts of GHG emissions from inputs in peanut production per hectare were calculated by using CO_2 emissions coefficients of agricultural inputs (Table 2) (Pishgar-Komleh *et al.,* 2012). The amount of produced CO_2 was calculated by multiplying the input application rate (diesel fuel, chemical fertilizers and biocide) by its corresponding emissions coefficient that is given in Table 2.

2.2. Selecting inputs for the ANN model and model development

ANNs are inspired to the human brain functionality and structure, which can be represented as a network of densely interconnected elements called neurons (Zangeneh *et al.,* 2011). Interest in using ANNs for sorting, modeling and forecasting has led to a tremendous surge in Agriculture research in the past. The first step of model creation for energy consumption and GHG emissions was finding appropriate variables (Safa and Samarasinghe, 2011). Peanut yield and GHG emissions were chosen as outputs of the developed model, while area and embedded energy (including human labor, machinery, diesel fuel, chemical fertilizers, biocides and seed) was selected as inputs of the model. Several structures were evaluated using the experimental data to determine the best prediction by the network. In this study, Levenberg-Marquardt learning Algorithm was applied to training ANNs. In mathematics and computing, the Levenberg-Marquardt Algorithm known as the damped least-squares method provides a numerical solution to the problem of minimizing a function, generally nonlinear, over a space of parameters of the function. These minimization problems arise especially in least squares curve fitting and nonlinear programming (Levenberg, 1944). The hidden layer creates a connection between input and output layers. Two neighboring layers are connected with links and each node in one layer is linked with all nodes of the next layer. The input weight matrix made all links between the input layer and hidden layers and the output weight matrix consists of the all links between the output and hidden layers. Weight (w) which controls the propagation value (x) and the output value (O) from each node is modified using the value from the preceding layer according to Eq. (7) (Zhao *et al.,* 2009):

$$O = f\left(T + \sum w_i x_i\right) \qquad (7)$$

where 'T' is a specific threshold (bias) value for each node. 'f ' is a non-linear sigmoid function, which increased uniformly.

In this paper, the differences between targeted and calculated outputs were determined error from end of testing processes. The back-propagation algorithm is used to find a local minimum of the error function. The network is initialized with randomly chosen weights. The gradient of the error function is computed and used to correct the initial weights. The error function can be expressed as (Deh Kiani *et al.,* 2010):

$$E = \frac{1}{p}\sum_{p}\sum_{k}\left(t_{pk} - z_{pk}\right)^2 \qquad (8)$$

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

The mean square error (MSE) of an estimator is one of many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated. The different models are compared using MSE. Also, the mean square error can show the networks capability for correct output prediction.

The MSE was described by Pahlavan *et al.* (2012):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i}^{n}\left(t_i - z_i\right)^2 \qquad (9)$$

where 't_i' and 'z_i' are the actual and the predicted output for the ith training vector, and '*N*' is the total number of training vectors.

The mean absolute percentage error (MAPE) and correlation coefficient (R) are used for characterizing the network performance. The coefficient of determination (R^2) is most often seen as a number between 0 and 1, used to describe how well a regression line fits a set of data. Mean relative error is the ratio of the size of an error to the size of the quantity. The R^2 and MAPE are expressed as follows:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2} \right) \quad (10)$$

$$MAPE(\%) = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{(t_i - z_i)}{t_i} \right| \quad (11)$$

where '*n*' is the number of the points in the data set, and '*t*' and '*z*' are actual output and predicted output sets, respectively (Tang and Yin, 2012).

2.3. Multi-objective genetic algorithm

Multi-objective optimization is an area of multiple criteria decision making that is concerned with mathematical optimization problems involving more than one objective function to be optimized simultaneously. In this research, energy consumption and GHG emissions were optimized by multi-objective genetic algorithm. In other word, the energy inputs should be allocated in a way so that the maximum yield and minimum greenhouse gas emissions are obtained. For this purpose, production functions was determined for both of output (peanut yield and GHG emissions) based energy inputs.

General form of the functions is as follows:

$$Y_i = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 + \alpha_5 X_5 + \alpha_6 X_6 + \alpha_7 X_7 + \alpha_8 X_8 + e_i \quad (12)$$

$$G_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + e_i \quad (13)$$

Where Xi stands for corresponding energies as 'X_1', human labor; 'X_2',machinery; 'X_3', diesel fuel; 'X_4', nitrogen; 'X_5', phosphate; 'X_6', potassium; 'X_7', biocides; 'X_8', seed, 'Y_i' peanut yield, and 'G_i' total GHG emissions.

Thereupon, the limits set for each function. Finally, multi-objective genetic algorithm method was applied for optimization by functions and their limits and optimal generations were determined. Moreover, the potential of GHG emissions was determined based results of optimization.

Results and discussion

Analysis of input–output energy use in peanut production

Table 3 represents the quantity of inputs and output used in three farm sizes of peanut production and their energy equivalents. The results revealed that the quantity of labor power required in the peanut production was 636.65 h ha^{-1}. The majority of human labor in the peanut production was used in the harvest and transportation operations. The total mean energy used in various farm operations during peanut production was 19248.04 MJ ha^{-1}. The highest average energy consumption of inputs was for nitrogen (8027.54MJ ha^{-1}) which was accounted for about 42% of the total energy input, followed by diesel fuel (6635.44 MJ ha^{-1}, 34.43%). The accurate utilization of chemical fertilizers and machinery management can lead to a significant reduction in direct use of diesel fuel energy and consequently it can improve the energy use efficiency without impairing yield or profitability. Canakci *et al.* (2005) calculated the energy inputs for maize at 11.36 GJ ha^{-1}. In some related studies total energy input has been reported as 18.93 GJ ha^{-1} for sunflower (Uzunoz *et al.,* 2008), 25.03 GJ ha^{-1} for barley (Mobtaker *et al.,* 2010), 18.02 GJ ha^{-1} for soybean in Golestan province of Iran (Ramedani *et al.*, 2011) and 53.80 GJ ha^{-1} for canola productions (Mousavi-Avval *et al.,* 2011b).

Table 4 illustrates the energy use efficiency (energy ratio), energy productivity, specific energy, net energy and energy intensiveness of peanut production based on different farm size levels. The energy use efficiency of 4.53 observed in the present study indicates that 4.53 times energy was produced per unit of energy used in peanut production. The energy ratio value of large farms (>3 ha) and medium farms (1-3 ha) with average value of 4.68 and 4.71 was significantly higher than its amount (4.29) in the small farms (<1 ha), respectively. In energy balances the energy ratio is often used as an index to examine the energy efficiency in crop production (Kuesters and Lammel, 1999). Also, specific energy was accounted as 5.52 MJ kg^{-1}. Energy use efficiency and specific energy are integrative indices indicating the potential environmental impacts associated with the production of crops (Mousavi-Avval *et al.,* 2011b). In other Studies, results for energy ratio have been reported for different crops such as 10.2 for cotton (Singh *et al.,* 2004), 0.66 for garlic (Samavatean *et al.,* 2010), 2.86 for barely (Mobtaker *et al.,* 2010), 1.16 for apple (Rafiee *et al.,* 2010), 0.64 for greenhouse cucumber (Mohammadi and Omid, 2010), 4.62 for soybean (Ramedani *et al.*, 2011) and 0.45 for wheat (Khoshnevisan *et al.,* 2013). The energy intensiveness and average energy productivity of peanut was computed 2.48 MJ $\$^{-1}$ and 0.18 kg MJ^{-1}, respectively. This means that 0.18 units output is obtained per unit energy.

Table 1. Energy equivalent of inputs and output in agricultural production.

Items	Unit	Energy equivalent ($MJ\ unit^{-1}$)	Reference
A. Inputs			
1. Human labor	h	1.96	(Mohammadshirazi *et al.*, 2012)
2. Machinery	kg yr[a]		
(a) Tractor and self-propelled		9-10	(Hatirli *et al.,* 2005)
(b) Implement and machinery		6-8	(Hatirli *et al.,* 2005)
3. Diesel fuel	L	56.31	(Mobtaker *et al.,* 2010)
4. Chemical fertilizers	kg		
(a) Nitrogen		66.14	(Mousavi-Avval *et al.,* 2011a)
(b) Phosphate (P_2O_5)		12.44	(Rafiee *et al.,* 2010)
(c) Potassium (K_2O)		11.15	(Unakitan *et al.,* 2010)
5. Biocides	kg	120	(Khoshnevisan *et al.,* 2013)
6. Seed	kg	25	(Kitani, 1999)
B. Output			
Peanut	kg	25	(Kitani, 1999)

[a] The economic life of machine (year).

Table 2. GHG emissions coefficients of agricultural inputs.

Input	Unit	GHG Coefficient ($kg\ CO_{2eq}\ unit^{-1}$)	Reference
1. Machinery	MJ	0.071	(Dyer and Desjardins, 2006)
2. Diesel fuel	L	2.76	(Dyer and Desjardins, 2003)
3. Chemical fertilizers	kg		
(a) Nitrogen		1.3	(Nabavi-Pelesaraei *et al.,* 2014)
(b) Phosphate (P_2O_5)		0.2	(Nabavi-Pelesaraei *et al.,* 2014)
(c) Potassium (K_2O)		0.2	(Pishgar-Komleh *et al.,* 2012)
4. Biocides	kg	6.3	(Lal, 2004)

The distribution of inputs used in the production of peanut according to the direct, indirect (DE vs. IDE), renewable and non-renewable energy (RE vs.NRE) groups for three farm sizes, are given in Table 4. The share of DE, IDE, RE and NRE of peanut production is exhibited in Fig. 1. It is seen that the direct and indirect energy resources are nearly equally utilized (41% and 59%), but it is also seen that the ratios of renewable and non-renewable energy are fairly different from each other (14.27% and 85.73%). Therefore, it is clear that non-renewable energy consumption was higher than that of renewable energy consumption in peanut production, in agreement with the literature for different crops (Yilmaz *et al.,* 2005; Erdal *et al.,* 2007; Kizilaslan,2009; Mobtaker *et al.,* 2012a).

GHG emissions of peanut production

The GHG emissions of inputs in peanut production based on three farm sizes are presented in Table 5. The amount of total GHG emissions was calculated as 571.18 $kgCO_{2eq.}$ ha^{-1}. The small and large farms had the highest and lowest GHG emissions from all peanut farms, respectively (580.94 and 520.29 $kgCO_{2eq.}$ ha^{-1}). Also, the difference between large and small farms was significant. Pathak and Wassmann (2007) calculated a total emissions of 1038 $kgCO_{2eq.}$ ha^{-1} for wheat production. Pishgar-Komleh *et al.* (2012) reported total emissions of 992.88 $kgCO_{2eq.}$ ha^{-1} for potato production. In other study, the total GHG emissions of wheat production was calculated 2711.58 $kgCO_{2eq.}$ ha^{-1} (Khoshnevisan *et al.,* 2013). Soni *et al.* (2013) determined CO_2 emissions of transplanted rice about 1100 $kgCO_{2eq.}$ ha^{-1}.

Table 3. Amounts of energy inputs and output in peanut production based on different farm size levels.

Items	Farm size groups (ha)			Average (MJ ha^{-1})	Percentage (%)
	Small (<1)	Medium (1-3)	Large (>3)		
A. Inputs					
1. Human labor	1175.14[a]	1378.25[b]	1138.17[c]	1247.83	6.48
2. Machinery	900.92[a]	750.04[b]	842.09[b]	842.53	4.38
3. Diesel fuel	6688.01[a]	6703.02[b]	5967.96[c]	6635.44	34.47
4. Chemical fertilizers					
(a) Nitrogen	8062.94[a]	8124.80[a]	7312.36[a]	8027.74	41.71
(b) Phosphate (P_2O_5)	324.27[a]	326.76[ab]	294.08[b]	322.85	1.68
(c) Potassium (K_2O)	352.32[a]	355.02[ab]	319.52[b]	350.78	1.82
5. Biocides	364.88[a]	299.91[a]	262.85[a]	321.09	1.67
6. Seed	1424.07[a]	1583.06[ab]	1491.11[b]	1499.78	7.79
The total energy input	19292.55[a]	19520.86[a]	17628.14[a]	19248.04	100
B. Output					
Peanut	82763.73[a]	92024.97[b]	82442.20[c]	87209.68	

Note: Different letters show significant difference of means at 5% level.

Table 4. Energy input–output ratio in peanut production based on different farm size levels.

Items	Unit	Farm size groups (ha)			Average	Percentage (%)
		Small (<1)	Medium (1-3)	Large (>3)		
Energy use efficiency	-	4.29[a]	4.71[b]	4.68[b]	4.53	-
Energy productivity	kg MJ^{-1}	0.17[a]	0.19[b]	0.19[c]	0.18	-
Specific energy	MJ kg^{-1}	5.83[a]	5.30[b]	5.35[c]	5.52	-
Net energy gain	MJ ha^{-1}	63471.17[a]	72504.11[b]	64814.05[c]	67961.64	-
Energy intensiveness	MJ $\$^{-1}$	1.67[a]	1.52[b]	1.53[b]	1.58	-
Direct energy[d]	MJ ha^{-1}	7863.14[a]	8081.27[b]	7106.13[c]	7883.27	40.96
Indirect energy[e]	MJ ha^{-1}	11429.41[a]	11439.59[a]	10522.01[a]	11364.77	59.04
Renewable energy[f]	MJ ha^{-1}	2599.22[a]	2961.32[b]	2629.29[b]	2747.62	14.27
Non-renewable energy[g]	MJ ha^{-1}	16693.33[a]	16559.54[a]	14998.85[a]	16500.42	85.73
Total energy input	MJ ha^{-1}	19292.55[a]	19520.86[a]	17628.14[a]	19248.04	100

Note: Different letters show significant difference of means at 5% level.

[d] Includes human labor, diesel fuel.

[e] Includes seed, chemical fertilizers, biocides, machinery.

[f] Includes human labor, seed.

[g] Includes diesel fuel, Biocides, chemical fertilizers, machinery.

Evaluation and analysis of model

In this study, several Multi-layer perceptron (MLP) networks were designed, trained and generalized, using the Matlab 7.2 (R2012a) software package. The Levenberg-Marquardt networks were trained using the training sets formed by including 60 percent of data. The Levenberg-Marquardt algorithm were tested applying the testing datasets including 48 samples. The experimental tests consisted of nine inputs and two outputs. Also, the different farm size levels were one of the inputs as area. In this paper, an input layer with nine input variables, one hidden layer with twenty-two neurons and an output layer with two output variables gained the best results (9-22-2 structure). The highest R^2 was calculated by the best topology for yield and GHG emissions of peanut production (Table 6). Also, this topology had the lowest value of RMSE and MAPE, indicating that the predicted peanut yield and CO_2 emissions by the ANN model tend to follow the corresponding actual ones quite closely (Khoshnevisan *et al.,* 2013).

Table 5. GHG emissions of inputs in peanut based on different farm size levels.

Items	Farm size groups (ha)			Average (kg $CO_{2eq.}$ ha^{-1})	Percentage (%)
	Small (<1)	Medium (1-3)	Large (>3)		
1. Machinery	63.97^a	53.25^b	59.79^b	59.82	10.47
2. Diesel fuel	327.81^a	328.54^b	292.52^b	325.23	56.94
3. Chemical fertilizers					
(a) Nitrogen	158.48^a	159.70^b	143.73^c	157.79	27.62
(b) Phosphate (P_2O_5)	5.21^a	5.25^a	4.73^a	5.19	0.91
(c) Potassium (K_2O)	6.32^a	6.37^b	5.73^c	6.29	1.11
4. Biocides	19.16^a	15.75^a	13.80^a	16.86	2.95
Total GHG emissions	580.94^a	568.86^b	520.29^b	571.18	100

Note: Different letters show significant difference of means at 5% level.

Table 6. The best result of different arrangement of models.

Item	Peanut yield	GHG emissions
R^2	0.994	0.999
RMSE	0.076	0.003
MAPE	0.174	0.009

Pahlavan *et al.* (2012) 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. In another study, the final model of ANN predicted the energy consumption based on farm conditions (size of crop area), farmers' social considerations (level of education), and energy inputs (N and P use and irrigation frequency), and it predicts energy use in Canterbury arable farms with an error margin of 12% (± 2900 MJ ha^{-1}) (Safa and Samarasinghe, 2011). Khoshnevisan *et al.* (2013) developed an ANN model with one input layer, two hidden layers and two output layer that can predict GHG emissions and energy consumption for wheat production in Esfahan province, Iran.

Table 7. Sensitivity analysis results for input energies.

Items	Peanut yield	CO_2 emissions
Area	0.222	0.085
Human labor	0.196	0.070
Machinery	0.127	0.007
Diesel Fuel	0.012	0.080
Nitrogen	0.010	0.150
Phosphate	0.045	0.250
Potassium	0.112	0.152
Biocides	0.055	0.017
Seed	0.464	0.086

Table 8. Limits of functions for multi-objective genetic algorithm (MJ ha^{-1}).

$662.32 \le X_1 \le 2323.76$	$98.78 \le X_5 \le 746.15$
$150.48 \le X_2 \le 2257.20$	$107.32 \le X_6 \le 810.68$
$1621.73 \le X_3 \le 16217.28$	$45.31 \le X_7 \le 827.44$
$2456.13 \le X_4 \le 18552.94$	$820.80 \le X_8 \le 2052.00$

The results of cross-correlation between predicted and observed output energy and GHG emissions are demonstrated in Fig. 2. The results disclosed that R calculated 0.997 and 0.999 for peanut yield and GHG emissions, respectively.

Table 9. Multi-objective genetic algorithm results for optimization of energy inputs and GHG emissions in peanut production.

Generation number	Optimum energy use (MJ ha^{-1})									Optimum GHG emissions (kg$CO_{2eq.}$ ha^{-1})						
	Human labor	Machinery	Diesel fuel	Nitrogen	Phosphate	Potassium	Biocides	Seed	Total energy use	Machinery	Diesel fuel	Nitrogen	Phosphate	Potassium	Biocides	Total GHG emissions
1	793	377	2308	18538	399	108	123	995	23640	26.74	113.12	364.36	6.41	1.93	6.46	519.03
2	919	200	1662	2525	101	753	76	1123	7358	14.20	81.46	49.62	1.62	13.51	4.00	164.42
3	925	200	1663	2800	103	750	74	1124	7639	14.21	81.49	55.04	1.65	13.45	3.90	169.74
4	833	214	1667	7689	101	480	75	925	11984	15.16	81.71	151.13	1.63	8.61	3.92	262.16
5	842	209	1669	3055	105	364	72	966	7281	14.80	81.78	60.05	1.69	6.53	3.79	168.64
6	866	213	1661	15679	103	131	83	933	19668	15.12	81.42	308.17	1.65	2.35	4.34	413.06
7	930	269	1742	18440	106	110	89	958	22644	19.11	85.39	362.45	1.70	1.98	4.69	475.32
8	820	255	1733	12016	106	131	89	959	16108	18.14	84.95	236.17	1.70	2.36	4.65	347.96
9	898	196	1673	2893	101	649	76	1033	7518	13.91	82.01	56.87	1.63	11.64	3.98	170.03
10	921	292	1878	18459	160	109	95	983	22897	20.75	92.04	362.81	2.57	1.95	4.99	485.12
11	908	205	1678	15516	102	142	82	1036	19669	14.56	82.26	304.97	1.64	2.55	4.30	410.28
12	854	207	1673	2859	102	606	73	968	7342	14.72	81.99	56.19	1.65	10.87	3.84	169.24
13	868	213	1668	7734	103	256	75	925	11841	15.10	81.74	152.02	1.65	4.58	3.94	259.03
14	793	377	2308	18538	399	108	123	995	23640	26.74	113.12	364.36	6.41	1.93	6.46	519.03
15	899	201	1664	2662	101	489	76	1051	7144	14.30	81.56	52.32	1.63	8.77	4.01	162.59
16	860	188	1662	16273	106	110	85	943	20228	13.34	81.48	319.86	1.70	1.98	4.48	422.83
17	892	205	1663	3222	101	465	76	1054	7678	14.58	81.50	63.33	1.62	8.33	4.00	173.36
18	807	201	1679	5266	103	539	76	1030	9701	14.25	82.32	103.51	1.65	9.67	3.98	215.39
19	878	214	1671	2689	102	204	74	1056	6888	15.18	81.89	52.85	1.64	3.66	3.87	159.08
20	853	235	1665	9139	103	135	81	930	13140	16.68	81.60	179.62	1.65	2.42	4.26	286.23
21	888	210	1692	6990	105	298	76	962	11220	14.89	82.94	137.39	1.68	5.34	4.01	246.26
22	854	230	1664	3014	103	207	80	1002	7154	16.30	81.57	59.24	1.65	3.72	4.19	166.68
23	802	248	1687	17191	116	113	83	942	21183	17.62	82.68	337.89	1.87	2.03	4.36	446.45
24	966	213	1681	3061	104	589	77	1124	7814	15.11	82.40	60.17	1.67	10.56	4.06	173.96
25	819	206	1682	4091	106	359	72	993	8329	14.66	82.45	80.40	1.70	6.45	3.80	189.45
26	907	206	1667	6881	101	194	77	1014	11048	14.60	81.69	135.25	1.63	3.49	4.05	240.71
27	901	217	1664	12907	103	169	75	979	17015	15.42	81.54	253.69	1.66	3.04	3.92	359.26
28	844	213	1661	8203	102	209	75	925	12231	15.10	81.40	161.23	1.64	3.75	3.95	267.07
29	786	325	2039	18453	403	108	84	1000	23197	23.10	99.92	362.69	6.48	1.94	4.42	498.54
30	850	260	1702	11486	103	149	70	982	15603	18.47	83.44	225.76	1.66	2.68	3.65	335.67
31	810	214	1662	12895	105	151	80	939	16855	15.17	81.45	253.46	1.68	2.71	4.20	358.67
32	859	214	1664	8418	103	164	77	943	12442	15.17	81.54	165.45	1.66	2.94	4.06	270.82
33	838	205	1679	7065	102	274	76	1033	11271	14.56	82.28	138.86	1.64	4.91	3.99	246.24
34	817	219	1664	16842	107	121	83	939	20792	15.53	81.58	331.04	1.72	2.18	4.35	436.39
35	862	207	1670	3002	102	449	74	1075	7441	14.73	81.84	59.00	1.64	8.06	3.87	169.14
36	835	213	1681	7553	102	382	79	952	11797	15.13	82.38	148.45	1.64	6.85	4.16	258.60
37	839	229	1709	5373	114	251	85	981	9582	16.25	83.76	105.61	1.84	4.51	4.48	216.44
38	907	207	1666	2759	110	465	82	1026	7222	14.72	81.65	54.23	1.77	8.35	4.28	164.99
39	840	212	1662	8897	101	154	83	959	12907	15.08	81.47	174.86	1.62	2.76	4.36	280.16
40	898	216	1664	7317	103	262	79	974	11514	15.32	81.57	143.82	1.66	4.70	4.17	251.23
41	921	292	1878	18459	160	109	258	983	23061	20.75	92.04	362.81	2.57	1.95	13.56	493.69
42	956	212	1666	3143	104	393	70	1034	7578	15.07	81.66	61.78	1.67	7.05	3.70	170.92

Sensitivity analysis

A sensitivity analysis was applied for assessing the predictive ability and validity of the developed models, using the best network selected (Table 7). The robustness of the model was determined by examining and comparing the output produced during the validation stage with the calculated values (Pahlavan *et al.,* 2012). Sensitivity analysis can show increased understanding of the relationships between input and output variables in a system or model. Sensitivity analysis provides insight into the usefulness of individual variables. With this kind of analysis it is possible to judge what parameters are the most significant (with sensitivity value close to 1) and the least significant (with sensitivity value close to 0) during generation of the satisfactory MLP (Pahlavan *et al.,* 2012). The results of sensitivity analysis revealed the seed had the highest sensitivity on peanut yield (0.464), followed by area and human labor. Also, the peanut yield had the lowest sensitivity to nitrogen energy.

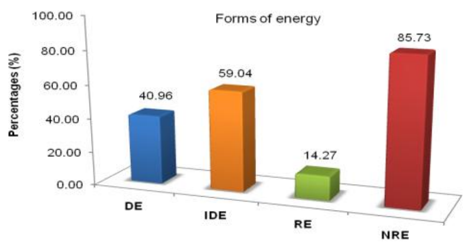

Fig. 1. The share of total mean energy inputs as direct (DE), indirect (IDE), renewable (RE) and non-renewable (NRE) forms.

Optimization of energy inputs and GHG emissions

After determination of energy inputs, GHG emissions and peanut yield for present farms, the functions calculated based Eq. (12) and (13) using the SPSS 20 software package.

The function can be expressed as the following relationship:

$$Y_i = -2.66 + 0.41X_1 + 0.25X_2 + 0.23X_3 - 7.36X_4 - 0.28X_5 + 7.62X_6 - 0.27X_7 + 1.25X_8 + e_i \quad (14)$$

$$G_i = -0.91 - 0.01X_1 + 0.06X_2 + 0.52X_3 + 0.52X_4 + 0.38X_5 - 0.51X_6 + 0.04X_7 - 0.01X_8 + e_i \quad (15)$$

Based the minimum and maximum rate of inputs usage, the limits of function were presented in Table 8.

In this research, the multi-objective genetic algorithm was applied to obtain maximum peanut yield and minimum GHG emissions using the Matlab 7.2 (R2012a) software package. The results of multi-objective genetic algorithm are given in Table 9. Accordingly, 42 optimal generations were calculated by multi-objective genetic algorithm (Table 9). In the next step, we selected the most efficient generation. For this purpose, the generation No. 19 selected as the most efficient generation because the total energy consumption and GHG emissions were the lowest in this generation toward other generations. The results of generation No. 19 revealed the total energy consumption and total GHG emissions was computed about 6888 MJ ha^{-1} and 159.08 $kgCO_{2eq.}$ ha^{-1}, respectively.

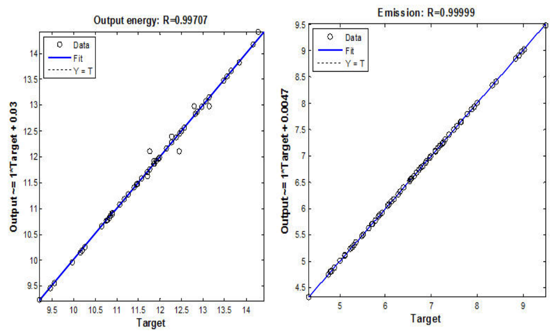

Fig. 2. Cross-correlation between predicted and observed output energy and GHG emissions.

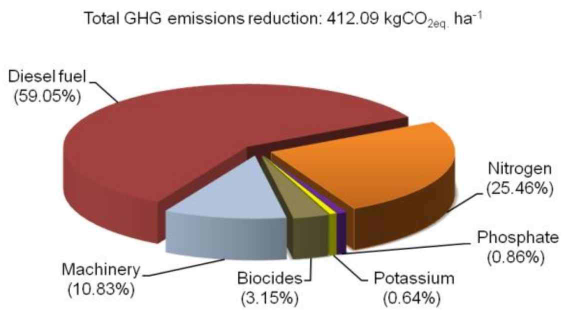

Fig. 3. Distribution of GHG emissions reduction for each input in peanut production.

Fig 3 displays the share of each input for potential of GHG emissions reduction. This figure indicated total GHG emissions reduction was found to be as 412.09 $kgCO_{2eq.}$ ha^{-1}. The highest share of GHG emissions reduction belonged to diesel fuel with 59.05%; followed by nitrogen (with 25.46%) and machinery (with 10..83%). Accordingly, the diesel fuel and nitrogen consumption should be reduced in peanut production. The selection of standard machinery, appropriate maintenance, applying organic farming system or the use of bio-fertilizers to reduction of chemical fertilizers (specially nitrogen) and reduction of tillage operations using minimum and no tillage methods can be closed the energy inputs and GHG emissions of present farms to optimal condition.

Conclusions

Based on the present study the following conclusions are drawn.

Peanut production consumed a total energy of 19248.04 MJ ha^{-1}, which was mainly due to chemical fertilizers. Energy output was calculated as 87209.68 MJ ha^{-1}. The output energy of medium farms for peanut production was higher than small and large farms significantly. Also, the difference of energy input was not significantly for three farm sizes of peanut production.

Energy use efficiency, energy productivity, specific energy, net energy and energy intensiveness were 4.53, 0.18 kg MJ^{-1}, 5.52 MJ kg^{-1}, 67937.21 MJ ha^{-1} and 1.58 MJ $\$^{-1}$, respectively.

The amount of direct and indirect forms of energies were 7883.27 (40.96%) and 11364.77 (59.04%) MJ ha^{-1} while the amount of renewable and non-renewable resources of energy were 2747.62 (14.27%) and 16500.42 (85.73%) MJ ha^{-1} , respectively.

The total GHG emissions of peanut production were calculated as 571.18 $kgCO_{2eq.}$ ha^{-1}. Also, the highest share of total GHG emissions belonged to with 56.94%. Furthermore, the small farm had the highest rate of total GHG emissions among three farm sizes with 580.94 $kgCO_{2eq.}$ ha^{-1}.

Using ANN for output energy and GHG emissions prediction revealed that the optimal network for this study were MLP with 9-22-2 topology and Levenberg-Marquardt training algorithm.

With respect to Levenberg-Marquardt training algorithm results, R^2 was 0.994 and 0.999, RMSE was 0.076 and 0.003 and MAPE was 0. 174 and 0.009 for peanut yield and GHG emissions in best topology, respectively. Furthermore, the cross-correlation for GHG emissions was more than peanut yield.

42 optimal generations were introduced by multi-objective genetic algorithm. The results of best generation revealed the total energy consumption and total GHG emissions were calculated about 6888 MJ ha^{-1} and 159.08 $kgCO_{2eq.}$ ha^{-1}, respectively. Comparison between present farms and optimal generation illustrated the diesel fuel had the highest share in total GHG emissions reduction with 59.09%.

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