Available online at http://www.ijabbr.com

International journal of Advanced Biological and Biomedical Research

Volume 1, Issue 11, 2013: 1478-1489

Modeling and optimization of energy inputs and greenhouse gas emissions for eggplant production using artificial neural network and multi-objective genetic algorithm

Ashkan Nabavi-Pelesaraei[1*], Sajjad Shaker-Koohi[2], Mohammad Bagher Dehpour[3]

[1] *Department of Agricultural Machinery Engineering, Faculty of Agriculture, University of Tabriz, Iran.*
[2] *Department of Agronomy and Plant Breeding, Faculty of Agriculture, University of Tabriz, Iran.*
[3] *Department of Agricultural Mechanization Engineering, Faculty of Agriculture, University of Guilan, Iran.*

ABSTRACT

This paper studies the modeling and optimization of energy use and greenhouse gas emissions of eggplant production using artificial neural network and multi-objective genetic algorithm in Guilan province of Iran. Results showed that the highest share of energy consumption belongs to diesel fuel (49.24%); followed by nitrogen (33.30%). The results indicated that a total energy input of 13910.67 MJ ha^{-1} was consumed for eggplant production. In ANN, the Levenberg-Marquardt Algorithm was examined to finding best topology for modeling and optimization of energy inputs an GHG emissions for eggplant production. The results of ANN indicated the best topology with 12-9-9-2 structure had the highest R^2, lowest RMSE and MAPE. Also, the multi-objective optimization was done by MOGA. In this research, 42 optimal was introduced by MOGA based minimum total GHG emissions and maximum yield of eggplant production, in the studied area. Also, the results revealed that the best generation with lowest energy use was consumed about 4597 MJ per hectare. The GHG emissions of best generation was calculated as about 127 kg $CO_{2eq.}$ ha^{-1}. The potential of GHG reduction by MOGA was computed as 388.48 kg $CO_{2eq.}$ ha^{-1}. Also, the highest reduction of GHG emissions belongs to diesel fuel with 65.05%.

Key words: Eggplant; Energy consumption; Greenhouse gas emissions; Modeling; Optimization.

1- INTRODUCTION

Eggplant (*Solanum melongena L.*), also known as Aubergine, Brinjal or Guinea squash is one of the nontuberous species of the night shade family Solanaceae (Kantharajah and Golegaonkar, 2004). Energy auditing can be used as building blocks for life-cycle assessments that include agricultural products, and can also serve as a first step towards identifying crop production processes that benefit most from increased efficiency (Hemmati et al., 2013). On the other hand agricultural production has been identified as a major contributor to atmospheric greenhouse gases (GHG) on a global scale with about 14% of

Corresponding Author E-mail: ashkan.nabavi@yahoo.com

global net CO_2 emissions coming from agriculture (IPCC, 2007). Practices on GHG emissions or to assess climate change mitigation measures (Dyer et al., 2010). Models are the only practical way to quantify the net effect of farm. 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 (Khoshnevisan et al., 2013a). 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. Recently, the number of scientists and engineers who are interested in modeling of energy consumption and related environmental impacts has been increased (Khoshnevisan et al., 2013b). Application of ANNs to estimate yield and GHG emissions of wheat production in Isfahan, Iran was reported by Khoshnevisan et al. (2013b). They used an ANN model with twelve input variables, one hidden layer with eight neurons and two outputs. Effective energy use in agriculture is one of the conditions for sustainable agricultural production, since it provides financial savings, fossil resources preservation and air pollution reduction (Nabavi-Pelesaraei et al., 2013a). multi-objective genetic algorithm (MOGA) is one main method for optimization in recent years. The genetic algorithm is an example of a search procedure that uses random selection for optimization of a function by means of the parameters space coding. The genetic algorithms were developed by Holland (1975) and the most popular references are perhaps Goldberg (1997) and a more recent one by Bäck (1996). Few research was done by genetic algorithm for optimization energy in agriculture, Hematian et al. (2013) investigated on optimization of energy consumption for sugar beet production. Their results indicated that the optimized total energy used for producing the sugar beet crops was 32716.06 MJ ha^{-1}. The main aim of this study was modeling of energy use and GHG emissions of eggplant production in Guialn province of Iran using ANN. Furthermore, the energy consumption and GHG emissions was optimized together by MOGA.

2- MATERIALS AND METHODS

2-1- Sampling design

This study was carried out in the eggplant farms located in Guilan province, Iran. Guilan province had the five place in producing eggplant in Iran (Ministry of Jihad-e-Agriculture of Iran, 2012). Guilan is located within 36◦ 34′ and 38◦ 27′ north latitude and 48◦ 53′ and 50◦ 34′ east longitude. Data were collected by using a face-to-face questionnaire performed in the production year 2012/2013. Average farm size was 0.5 ha in the area studied while the size of farms varied between 0.1 ha and 4 ha. From the villages in the area studied, farms were selected by using stratified sample randomly. The sample size was calculated using Cochran method (Mobtaker et al., 2010). It’s should be noted, the sample size was computed as 60. For determination of input and output energy, the energy standard coefficients were utilized. These coefficient are illustrated in Table 1. Also, energy equivalent for machinery is calculated by Eq.(1) (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 CO_2 emission coefficients that are shown in Table 2 were used to calculate the amounts of the GHG emissions from inputs in eggplant production per hectare. The application rate of machinery, diesel fuel, chemical fertilizers and biocides per hectare were multiplied by their corresponding emission coefficients which were taken from Table 2. The GHG coefficient of machinery input consists of manufacturing and applying the machinery on the farm (Pishgar-Komleh et al., 2013).

2-2- ANN design

ANN are data-processing systems inspired by biological neural system and are used to solve a wide variety of problems in science and engineering, particularly for some areas where the conventional modelling methods fail. A well-trained ANN can be used as a predictive model for a specific application. The predictive ability of an ANN results from the training on experimental data and then validation by independent data. An ANN has the ability to relearn to improve its performance if new data are available (Najafi et al., 2009). In this study, the modeling of energy consumption and GHG emissions was obtained from ANN. A typical ANN model consists of an input layer, one or more hidden layers and an output layer (Khoshnevisan et al., 2013c). Accordingly, the model was created based eight inputs including human labor, machinery, diesel fuel, nitrogen, phosphate, potassium, biocides and seed and two outputs covering output energy and total GHG emissions. The Levenberg-Marquardt learning Algorithm was applied to training ANN. All links between input layers and hidden layers composed the input weight matrix and all links between hidden layers and output layers composed the output weight matrix. 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. (2) (Zhao et al., 2009):

$$O = f\left(T + \sum w_i x_i\right) \tag{2}$$

where '*T*' is a specific threshold (bias) value for each node. '*f* ' is a non-linear sigmoid function, which increased monotonically. The performance of the trained networks was measured by root mean square error (RMSE), mean absolute percentage error (MAPE) and coefficient of determination (R^2) on another set of data (testing set), not seen by the network during training and cross-validation (CV), between the predicted values of the network and the target (or experimental) values.

The RMSE, MAPE and R^2 can be written as (Zangeneh et al., 2011):

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}} \sum_{i}^{n} \left(t_i - z_i\right)^2} \tag{3}$$

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{\left(t_i - z_i\right)}{t_i} \right| \tag{4}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2} \right) \quad (5)$$

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

2-3- Multi-objective genetic algorithm (MOGA)

Being a population-based approach, genetic algorithm are well suited to solve multi-objective optimization problems. A generic single-objective genetic algorithm can be modified to find a set of multiple non-dominated solutions in a single run. The ability of genetic algorithm to simultaneously search different regions of a solution space makes it possible to find a diverse set of solutions for difficult problems with non-convex, discontinuous, and multi-modal solutions spaces (Konak et al., 2006). The first step of optimization by MOGA was calculation of production functions. Based energy inputs and outputs (eggplant yield and total GHG emissions), the production functions was determined according to Eq. (6) and (7):

$$Y_i = a_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 + \alpha_5 X_5 + \alpha_6 X_6 + \alpha_7 X_7 + \alpha_8 X_8 + e_i \quad (6)$$

$$G_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + e_i \quad (7)$$

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' eggplant yield, and 'G_i' total GHG emissions.

Then, the limits of functions was calculated based minimum and maximum of energy consumption for each input.

Basic information on energy inputs and GHG emissions of eggplant production was entered into Excel 2010 spreadsheets, SPSS 20 and Matlab 7.2 (R2012a) software package.

3- RESULTS AND DISCUSSION

3-1- Analysis of input–output energy use in eggplant production

The amount of inputs and output energy used in eggplant production in the study area and percentage of each energy input in to total energy input for three groups of farm sizes are shown in Table 3. The results revealed the total energy inputs and output was computed as 13910.67 and 125612 MJ ha^{-1}, respectively. As is seen in Table 3, diesel fuel (with 49.24%) spent the most percentage of total energy input followed by nitrogen (with 33.30%) in this region for all three farms. The ANOVA results illustrated that the difference between three groups of farms wasn't significant in the 5% level. At first, it seems that farmers should try to reduce diesel fuel and nitrogen fertilizer consumptions in this region until the energy efficiency and energy productivity increases with total energy input reduction. Seed, potassium and had less share of total energy input, respectively. 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), 19.25 GJ ha^{-1} for peanut production in Guilan province, Iran (Nabavi-Pelesaraei et al., 2013b).

3-2- GHG emissions of eggplant production

The GHG emissions of different inputs was calculated by using the GHG conversion factors presented in Table 2. The results revealed that total emissions of eggplant production was 515.37 kg $CO_{2eq.}$ ha^{-1} (Table 4) from which machinery, diesel fuel, chemical fertilizers and biocides inputs, respectively. The highest share of emissions was belonged to diesel fuel with 65.14%; followed by nitrogen (with 17.67%) and machinery (with 11.17%). The ANOVA results showed The non-significant difference was found to be between three groups of farms. Also, the small and large farms had the highest and lowest rate of GHG emissions among all farms, respectively. Because, the emissions pattern of small farms (specially in diesel fuel and nitrogen consumption) should be closed to large farms. In a similar study, the diesel fuel and nitrogen had the highest share for GHG emissions in wheat production of Isfahan, Iran (Ghahderijani et al., 2013).

3-3- Evaluation and analysis of model

The Levenberg-Marquardt algorithm was applied for modeling of eggplant yield and GHG emissions based energy inputs. The ANN model with twelve neuron in input layers, two hidden layer with 9 neuron for each layer and two outputs (best structure: 12-9-9-2) was determined as best structure, in this study. The results of best topology are given in Table 5. The results disclosed the determination of coefficient for yield and GHG emissions of eggplant production was calculated as 0.963 and 0.988, respectively. Also, the rate of RMSE was found to be 0.056 and 0.023 for eggplant yield and GHG emissions, respectively.

Rahman and Bala (2010) reported that a model consisted 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 topology for predicting jute production in Bangladesh. Safa and Samarasinghe (2011) developed an ANN model based on a modular neural network with two hidden layers that could 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 that ANN model is more viable to predict energy consumption in wheat production rather than regression models. In another study, Khoshnevisan et al. (2013b) reported that a model consisted of an input layer with twelve neurons, one hidden layer with 8 neurons and the output layer with two variables was the best topology for predicting basil production in Esfahan province of Iran.

3-4- Optimization of energy inputs and GHG emissions

The model of yield and GHG emissions was optimized by MOGA based energy inputs. The limitation of energy inputs are demonstrated in Table 6. The minimum consumption was considered as lower limit; While the maximum quantity of energy for each input was determined as higher limit.

Also, the productions function was calculated based Eq. (6) and (7):

$$Y_i = 4.73 + 0.44X_1 + 0.26X_2 + 0.32X_3 - 0.40X_4 - 0.40X_5 - 0.42X_6 - 0.02X_7 + 1.26X_8 + e_i \quad (8)$$

$$G_i = -1.11 - 0.02X_1 + 0.60X_2 + 0.59X_3 + 0.96X_4 + 0.96X_5 + 0.31X_6 + 0.05X_7 - 0.01X_8 + e_i \quad (9)$$

In this study, the MOGA was computed 42 optimal generation based maximum eggplant yield and minimum total GHG emissions (Table 7). Moreover, the best generation was determined based minimum energy consumption in this study. Accordingly, No. 28 was selected as efficient generation for the studied area. In another words, this generation had the maximum yield, minimum GHG emissions and minimum energy consumption for eggplant production in Guilan province of Iran. The total energy consumption and GHG emissions of best generation was found to be about 4597 MJ ha^{-1} and 127 $kgCO_{2eq.}$ ha^{-1}, respectively.

In the last part of this study, the potential of GHG reduction by MOGA was calculated. Fig 1 displays the share of each input for total GHG reduction. Based the results, diesel fuel (with 65.05%) had the highest percentages in GHG reduction; followed by nitrogen (with 16.25%) and machinery (with 12.25%). With respect to results, it's suggested, in the first step, the diesel fuel consumption and machinery should be reduced by timely maintenance and selection of appropriate machinery. Also, the applying minimum tillage, no tillage system and bio-fertilizers instead conventional tillage and chemical fertilizers can be reduced energy consumption and GHG emissions in the studied area, significantly.

4- CONCLUSION

The main objective of this study was to model and optimize yield (or output energy) and GHG emissions of eggplant production in the Guilan province of Iran. The results revealed that the total input and output energies in eggplant production were 13910.67 and 125612.00 MJ ha^{-1}, respectively and simultaneously the total GHG emissions was 515.37 kg $CO_{2eq.}$ ha^{-1}. Based on the results, diesel fuel was the most influential factor in energy consumption and GHG emissions. For eggplant production, the ANN model with 12-9-9-2 structure was the best model for forecasting the output energy and GHG emissions. For the best topology RMSEs were 0.056 and 0.023, MAPEs were 0.105 and 0.010 for output energy and GHG emissions, respectively. Moreover, the R^2 was calculated as 0.963 and 0.988 for energy and GHG emissions modeling, respectively. The results of multi-objective optimization showed the MOGA was apprised 42 generation containing maximum yield and minimum total GHG emissions as optimal units; But the best generation was selected based minimum energy consumption. The total energy use and GHG emissions of best generation was evaluated about 4597 MJ ha^{-1} and 127 kg $CO_{2eq.}$ ha^{-1}. Also, the highest share of GHG reduction was belonged to diesel fuel with 65.05%. So, the selection of standard machinery can be saved the energy consumption and reduce the GHG emissions, significantly.

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

Items (unit)	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, 2011)
(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	(Nabavi-Pelesaraei et al., 2013b)
6. Seed	kg	5.9	(Kitani, 1999)
B. Output			
Eggplant	kg	5.9	(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., 2013a)
(b) Phosphate (P_2O_5)		0.2	(Nabavi-Pelesaraei et al., 2013a)
(c) Potassium (K_2O)		0.2	(Pishgar-Komleh et al., 2013)
4. Biocides	kg	6.3	(Lal, 2004)

Table 3.
Amounts of energy inputs and output in eggplant 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	678.92[a]	645.53[b]	581.13[c]	637.12	4.58
2. Machinery	953.50[a]	777.74[b]	810.50[b]	810.93	5.83
3. Diesel fuel	7768.86[a]	6858.17[b]	6160.41[c]	6849.41	49.24
4. Chemical fertilizers					
(a) Nitrogen	5226.90[a]	4626.92[a]	4219.21[a]	4631.98	33.30
(b) Phosphate (P_2O_5)	420.43[a]	372.17[ab]	339.37[b]	372.58	2.68
(c) Potassium (K_2O)	217.48[a]	192.52[ab]	175.55[b]	192.73	1.39
5. Biocides	445.14[a]	427.49[a]	336.62[a]	411.20	2.96
6. Seed	4.71[a]	4.73[ab]	4.69[b]	4.72	0.03
The total energy input	15715.96[a]	13905.27[a]	12627.49[a]	13910.67	100
B. Output					
Eggplant	13582.16[a]	125580.93[b]	118745.18[c]	125612.00	

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

Table 4.
GHG emissions of inputs in eggplant 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	67.70[a]	55.22[b]	57.55[a]	57.58	11.17
2. Diesel fuel	380.79[a]	336.15[b]	301.95[a]	335.72	65.14
3. Chemical fertilizers					
(a) Nitrogen	102.74[a]	90.94[b]	82.93[a]	91.04	17.67
(b) Phosphate (P_2O_5)	6.76[a]	5.98[a]	5.46[a]	5.99	1.16
(c) Potassium (K_2O)	3.90[a]	3.45[b]	3.15[a]	3.46	0.67
4. Biocides	23.37[a]	22.44[a]	17.67[a]	21.59	4.19
Total GHG emissions	585.25[a]	514.19[b]	468.70[a]	515.37	100

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

Table 5.
The best result of different arrangement of models.

Item	Eggplant yield	GHG emissions
R^2	0.963	0.988
RMSE	0.056	0.023
MAPE	0.105	0.010

Table 6.
Limits of functions for multi-objective genetic algorithm (MJ ha^{-1})

$338.17 \leq X_1 \leq 1186.48$	$113.99 \leq X_5 \leq 861.06$
$144.84 \leq X_2 \leq 2172.54$	$58.97 \leq X_6 \leq 445.42$
$1674.02 \leq X_3 \leq 16740.23$	$58.03 \leq X_7 \leq 1059.68$
$1417.18 \leq X_4 \leq 10174.99$	$2.58 \leq X_8 \leq 6.46$

Table 7.
Multi-objective genetic algorithm results for optimization of energy inputs and GHG emissions in eggplant production.

Generation number	Optimum energy use (MJ ha^{-1})									Optimum GHG emissions (kgCO$_{2eq.}$ 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	1177	2142	16235	1461	120	59.1	78.5	6.46	21280	152	796	28.7	1.93	1.06	4.12	984
2	1179	187	12629	1423	115	59.6	64.0	6.45	15664	13	619	28.0	1.85	1.07	3.36	667
3	1177	2142	16235	1461	120	59.1	78.5	6.46	21280	152	796	28.7	1.93	1.06	4.12	984
4	1155	145	1765	1421	115	59.2	59.3	6.23	4725	10	87	27.9	1.84	1.06	3.11	131
5	1177	1503	15622	1434	116	59.5	64.7	6.45	19983	107	766	28.2	1.87	1.07	3.39	907
6	1168	2038	14355	1474	116	60.3	70.5	6.45	19288	145	704	29.0	1.87	1.08	3.70	884
7	1104	150	1691	1419	114	59.3	59.8	5.93	4602	11	83	27.9	1.84	1.06	3.14	127
8	1162	185	2512	1424	115	59.5	63.0	6.44	5526	13	123	28.0	1.85	1.07	3.31	170
9	1167	210	13612	1432	116	59.4	66.2	6.44	16669	15	667	28.1	1.87	1.07	3.48	717
10	1134	163	4475	1428	115	59.5	61.9	6.45	7443	12	219	28.1	1.86	1.07	3.25	265
11	1179	380	12727	1424	115	59.4	66.2	6.44	15957	27	624	28.0	1.85	1.07	3.48	685
12	1136	219	5231	1430	115	59.5	61.0	6.39	8257	16	256	28.1	1.84	1.07	3.20	306
13	1145	189	3496	1424	115	59.4	62.9	6.43	6497	13	171	28.0	1.85	1.07	3.30	219
14	1175	1265	13422	1460	116	59.4	71.5	6.46	17575	90	658	28.7	1.86	1.06	3.76	783
15	1168	242	15440	1434	115	59.7	64.0	6.45	18529	17	757	28.2	1.86	1.07	3.36	808
16	1107	155	2017	1425	115	59.6	60.1	6.27	4946	11	99	28.0	1.85	1.07	3.15	144
17	1167	971	13656	1434	116	59.6	64.0	6.45	17474	69	669	28.2	1.87	1.07	3.36	773
18	1153	199	2940	1422	115	59.3	60.1	6.34	5954	14	144	27.9	1.86	1.06	3.15	192
19	1178	219	13834	1431	115	59.6	64.0	6.45	16907	16	678	28.1	1.86	1.07	3.36	728
20	1105	161	1797	1424	115	61.6	61.7	6.34	4731	11	88	28.0	1.85	1.10	3.24	134
21	1108	159	2094	1428	115	59.5	59.7	6.40	5030	11	103	28.1	1.85	1.07	3.14	148
22	1104	145	1691	1419	114	59.2	58.9	5.93	4597	10	83	27.9	1.84	1.06	3.09	127
23	1144	186	5058	1425	115	59.8	62.8	6.44	8058	13	248	28.0	1.85	1.07	3.30	295
24	1171	1625	12600	1439	116	59.5	64.6	6.45	17082	115	618	28.3	1.86	1.07	3.39	768
25	1161	168	2301	1431	115	59.4	62.6	6.36	5305	12	113	28.1	1.85	1.07	3.29	159
26	1175	1189	12794	1431	115	59.4	66.5	6.45	16837	84	627	28.1	1.86	1.07	3.49	746
27	1165	448	14217	1433	115	59.5	64.4	6.45	17509	32	697	28.2	1.86	1.07	3.38	763
28	**1104**	**145**	**1691**	**1419**	**114**	**59.2**	**58.9**	**5.93**	**4597**	**10**	**83**	**27.9**	**1.84**	**1.06**	**3.09**	**127**
29	1143	221	11844	1429	115	59.8	64.4	6.43	14883	16	581	28.1	1.85	1.07	3.38	631
30	1152	187	4596	1423	115	59.4	61.5	6.43	7599	13	225	28.0	1.85	1.06	3.23	273
31	1174	935	12638	1426	115	59.5	66.5	6.45	16422	66	619	28.0	1.86	1.07	3.49	720
32	1164	402	13076	1429	115	59.4	64.6	6.45	16317	29	641	28.1	1.85	1.07	3.39	704
33	1166	586	13747	1433	116	59.6	64.3	6.45	17178	42	674	28.2	1.86	1.07	3.38	750
34	1179	411	14285	1433	116	59.4	64.8	6.44	17555	29	700	28.2	1.86	1.07	3.40	764
35	1141	436	8550	1427	115	59.6	63.9	6.44	11800	31	419	28.1	1.85	1.07	3.36	484
36	1171	769	13222	1432	116	59.6	65.2	6.44	16842	55	648	28.2	1.86	1.07	3.42	737
37	1167	194	6417	1425	115	59.6	63.8	6.44	9448	14	315	28.0	1.85	1.07	3.35	363
38	1151	193	5283	1428	116	59.4	62.3	6.45	8299	14	259	28.1	1.87	1.07	3.27	307
39	1164	341	12464	1428	116	59.8	63.3	6.45	15641	24	611	28.1	1.86	1.07	3.32	669
40	1177	2126	14906	1455	121	59.4	78.0	6.46	19930	151	731	28.6	1.95	1.07	4.09	917
41	1169	2006	13705	1441	116	60.3	69.1	6.45	18573	142	672	28.3	1.86	1.08	3.63	849
42	1153	182	2865	1422	115	59.3	60.1	6.29	5863	13	140	27.9	1.86	1.06	3.15	187

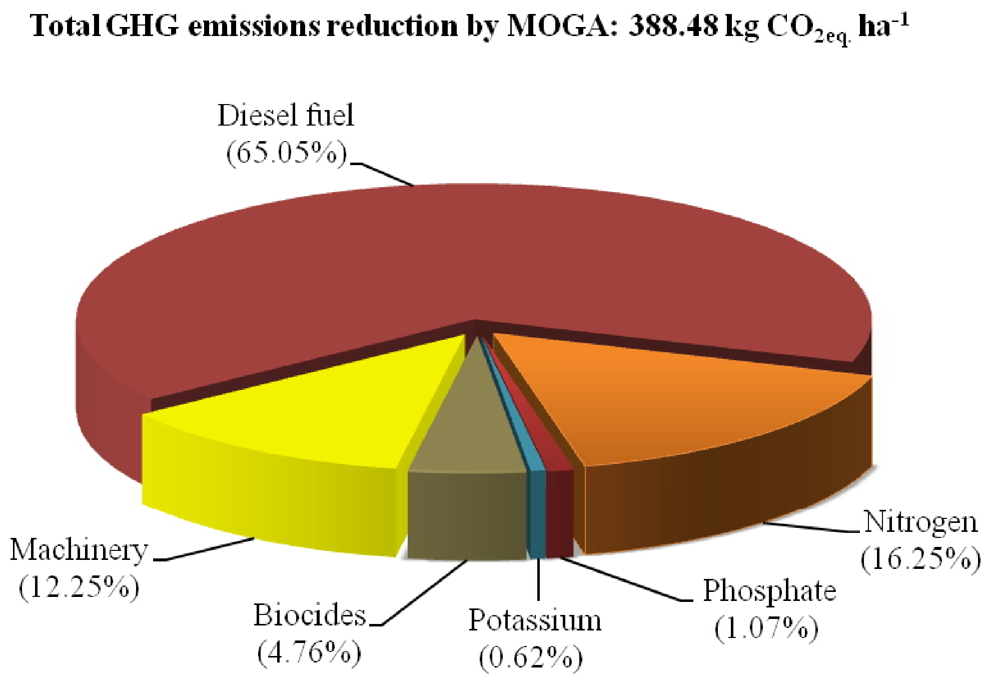

Fig. 1. Distribution of GHG emissions reduction for each input in eggplant production.

ACKNOWLEDGMENT

The financial support provided by the University of Tabriz, Iran, is duly acknowledged. Also, I want to express my deep appreciation of all Ms. Fatemeh Mostashari-Rad's making effort to help me revise the study.

REFERENCES

Kantharajah, AS., & Golegaonkar, PG. (2004). Somatic embryogenesis in eggplant Review. Scientia Horticulturae. 99: 107-117.

Hemmati, A., Tabatabaeefar, A., & Rajabipour, A. (2013). Comparison of energy flow and economic performance between flat land and sloping land olive orchards. Energy. 61:472-478.

IPCC. (2007). IPCC Assessment Report 4. <www.ipcc.ch>.

Dyer, J.A., Kulshreshtha, S.N., McConkey, B.G., & Desjardins, R.L. (2010). An assessment of fossil fuel energy use and CO_2 emissions from farm field operations using a regional level crop and land use database for Canada. Energy. 35: 2261-2269.

Khoshnevisan, B., Rafiee, S., Omid, M., & Mousazadeh, H. (2013a). Developing an artificial neural networks model for predicting output energy and GHG emission of strawberry production. International Journal of Applied Operational Research. 3(4): 43-54.

Khoshnevisan, B., Rafiee, S., Omid, M., Mousazadeh, H., & Rajaeifar, M.A. (2013b). Application of artificial neural networks for prediction of output energy and GHG emissions in potato production in Iran. Agricultural Systems. 123: 120-127.

Nabavi-Pelesaraei, A., Abdi, R., Rafiee, S., & Mobtaker, HG. (2013a). Optimization of energy required and greenhouse gas emissions analysis for orange producers using data envelopment analysis approach. Journal of Cleaner Production. http://dx.doi.org/10.1016/j.jclepro.2013.08.019.

Holland, J.H. (1975). Adaptive in Natural and Artificial Systems. Ann Arbor, MI: University of Michigan Press.

Goldberg, D.E. (1997). Genetic Algorithms, in Search, Optimization & Machine Learning. Addison Wesley.

Bäck, T. (1996). Evolutionary Algorithms in Theory and Practice: Evolution Strategies, Evolutionary Programming, Genetic Algorithms. Oxford University Press.

Hematian, A., Bakhtiari, A.A., Yaghubi, O., & Zarei-Shahamat, E. (2013). Optimization of Energy Consumption in Sugar-Beet Production Using Genetic Algorithm “A Case study in Kermanshah Province, Iran”. International journal of Agronomy and Plant Production. 4(6): 1351-1356.

Ministry of Jihad-e-Agriculture of Iran. 2012. Annual Agricultural Statistics. www.maj.ir (in Persian).

Mobtaker, HG., Keyhani, A., Mohammadi, A., Rafiee, S., & Akram, A. (2010). Sensitivity analysis of energy inputs for barley production. Agriculture, Ecosystems and Environment. 137: 367-372.

Hatirli, SA., Ozkan, B., & Fert, C. (2005). An econometric analysis of energy input-output in Turkish agriculture. Renewable and Sustainable Energy Reviews. 9: 608-623.

Mohammadshirazi, A., Akram, A., Rafiee, S., Mousavi-Avval, SH., & Bagheri Kalhor, E. An analysis of energy use and relation between energy inputs and yield in tangerine production. Renewable and Sustainable Energy Reviews. 16: 4515-4521.

Mousavi-Avval, SH., Rafiee, S., Jafari, A., & Mohammadi, A. (2011). Optimization of energy consumption for soybean production using Data Envelopment Analysis (DEA) approach. Applied Energy. 88: 3765-3772.

Rafiee, S., Mousavi-Avval, SH., & Mohammadi, A. (2010). Modeling and sensitivity analysis of energy inputs for apple production in Iran. Energy. 35: 3301-3306.

Unakitan, G., Hurma, H., & Yilmaz, F. (2010). An analysis of energy use efficiency of canola production in Turkey. Energy. 35: 3623-3627.

Nabavi-Pelesaraei, A., Abdi, R., & Rafiee, S. (2013b). Energy use pattern and sensitivity analysis of energy inputs and economical models for peanut production in Iran. International Journal of Agriculture and Crop Sciences. 5(19): 2193-2202.

Kitani, O. (1999). Energy and biomass engineering. In: CIGR handbook of agricultural engineering. St. Joseph, MI: ASAE.

Dyer, JA., & Desjardins, RL. (2006). Carbon dioxide emissions associated with the manufacturing of tractors and farm machinery in Canada. Biosystems Engineering. 93(1): 107-118.

Dyer, JA., & Desjardins, RL. (2003). Simulated farm fieldwork, energy consumption and related greenhouse gas emissions in Canada. Biosystems Engineering. 85(4): 503-513.

Pishgar-Komleh, SH., Omid, M., & Heidari, MD. (2013). On the study of energy use and GHG (greenhouse gas) emissions in greenhouse cucumber production in Yazd province. Energy. 59: 63-71.

Lal, R. (2004). Carbon emission from farm operations. Environment International. 30(7): 981-990.

Najafi, G., Ghobadian, B., Tavakoli, T., Buttsworth, D.R., Yusaf, TF., & Faizollahnejad, M. (2009). Performance and exhaust emissions of a gasoline engine with ethanol blended gasoline fuels using artificial neural network. Applied Energy. 86: 630-639.

Khoshnevisan, B., Rafiee, S., Omid, M., & Mousazadeh, H. (2013c). Prediction of potato yield based on energy inputs using multi-layer adaptive neuro-fuzzy inference system. Measurement. 47: 521-530.

Zhao, Z., Chow, TL., Rees, HW., Yang, Q., Xing, Z., & Meng, FR. (2009). Predict soil texture distributions using an artificial neural network model. Computers and Electronics in Agriculture 65(1): 36-48.

Zangeneh, M., Omid, M., & Akram, A. (2011). A comparative study between parametric and artificial neural networks approaches for economical assessment of potato production in Iran. Spanish Journal of Agricultural Research. 9(3): 661-671.

Konak, A., Coit, D.W., & Smith, A.E. (2006). Multi-objective optimization using genetic algorithms: A tutorial. Reliability Engineering and System Safety. 91: 992-1007.

Uzunoz, M., Akcay, Y., & Esengun, K. (2008). Energy input-output analysis of sunflower seed (*Helianthus annuus L.*) oil in Turkey. Energy Sources Part B-Economics. Planning and Policy. 3: 215-223.

Ramedani, Z., Rafiee, S., & Heidari, M.D. (2011). An investigation on energy consumption and sensitivity analysis of soybean production farms. Energy. 36: 6340-6344.

Ghahderijani, M., Pishgar-Komleh, S.H., Keyhani, A., & Sefeedpari, P. (2013). Energy analysis and life cycle assessment of wheat production in Iran. African Journal of Agricultural Research. 8(18): 1929-39.

Rahman, MM., & Bala, BK. (2010). Modelling of jute production using artificial neural networks. Biosystems Engineering. 105(3): 350-356.

Safa, M., & Samarasinghe, S. (2011). Determination and modelling of energy consumption in wheat production using neural networks: "A case study in Canterbury province, New Zealand". Energy. 36(8): 5140-5147.