Available online www.jsaer.com

Journal of Scientific and Engineering Research, 2016, 3(1):97-105

Research Article

ISSN: 2394-2630
CODEN(USA): JSERBR

Determination of Energy and Economic Indicators and Modeling of Output Energy for Maize Production using Artificial Neural in Shooshtar, Iran

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Abstract The aims of this study were to determine energy (input-output) and energy cost analysis and prediction of output energy for maize production in Shooshtar County of Iran, Data were collected from 40 maize farms by using a face to face questionnaire method in 2015. The results revealed that in maize production, total energy input was 39303.91 MJ/ha. The highest share of energy consumed was recorded for N fertilizer (38.83%) which is a nonrenewable resource. Output Energy was 58077.41 MJ/ha. Accordingly, energy efficiency was 1.47, energy productivity calculated as 0.10 $KgMJ^{-1}$ and specific energy was observed as 9.94 $MJKg^{-1}$. The results also revealed that benefit to cost ratio (1.80); indicating a better management of energy and input consumptions in these farms. The artificial neural network model with (5-17-2) structure was the best model for predicting the amount of energy output. In the best topology, the (R) was calculated as 0.999 and 0.989 for train and test, respectively.

Keywords Energy efficiency, benefit to cost ratio, Maize production, Artificial neural network, Shoostar

Introduction

Maize is the most widely grown crop in the Iran with 1,650,000 tons in a cropping area of 225,000 ha [1]. Energy has been a key input of agriculture since the age of subsistence agriculture. It is an established fact worldwide that agricultural production is positively correlated with energy input [2]. Agriculture is both a producer and consumer of energy. Energy input–output analysis is usually used to evaluate the efficiency and environmental impacts of production systems [3]. Energy use in agriculture has been increasing in response to increasing population, limited supply of arable land and a desire for higher standards of living [4]. In mother agriculture system input energy is very much more than traditional agriculture system, but energy use efficiently has been redacting in response to no affective use of input energy. Efficient use of energies helps to achieve increased production and productivity and contributes to the economy, profitability and competitiveness of agriculture sustainability in rural areas [5]. Scientific forecasts and analysis of energy consumption will be of great importance for the planning of energy strategies and policies [6]. The relation between agriculture and energy is very close. Agriculture itself is an energy user and energy supplier in the form of bio-energy [7]. Energy consumption in developing countries has been increasing rapidly due to recent economic growth and development [8]. However, increased input use in agricultural production may not bring maximum profits due to increasing production costs [9]. Furthermore, intensive use of energy causes problems threatening public health and the environment. Efficient use of energy is one of the principal requirements for sustainable agricultural productions [10]. It will minimize environmental problems and improve sustainable agriculture as an economical production system. The development of agricultural systems with low input of energy compared to the output of food would result in improvement of energy use efficiency and reduction of the environmental impacts. Improving the energy efficiency not only helps in improving competitiveness through cost reduction but also results in minimized energy-related environmental pollution, thus positively contributing towards sustainable development [11]. The energy input-output analysis is usually made to evaluate the efficiency and environmental impacts of production systems. This analysis will determine how efficient the energy is used. In recent years, many researchers have investigated the energy use for agricultural productions [12]. On the other hand, create a model between input energy and energy output will give useful information from the impact of each of the inputs into performance the products [13]. Today, the use of artificial intelligence for modeling a variety of fields, including energy and the environment is growing. Modeling with artificial neural network is one of the useful methods that for solving a variety of complex problems, Non-understandable or require very high resources in comparison with the old computational methods has been shown quite useful [14]. Moreover, in some studies the effect of farm size on energy use efficiency of agricultural production was investigated; Esengun et al. (2010) examined the dry apricot production in different farm sizes in terms of energy use efficiency and economical analysis [15]. They reported that, both the total energy input and output energy in apricot production decreased when farm size increased; while, the energy use efficiency and energy productivity increased when farm size increased. Yilmaz et al. (2005) investigated the effect of farm size on energy use and input costs for cotton production in Turkey; from this study it was found that large farms were more successful in energy productivity, use efficiency and economic performance; also, it was concluded that energy management at farm level could be improved to give more efficient and economic use of energy [16]. Cetin and Vardar (2008) investigated the energy consumption in small, medium and large farms of tomato production; they concluded that large farms were more successful in terms of energy use and economic performance [17]. Zangeneh et al. (2010) developed an Artificial Neural Network model to predict mechanization indices based on energy and power consumption [18]. Results showed that the best model for this study had a 13-4-1 configuration. The values of the optimum model's outputs correlated well, with R2 of 0.98. Value of MAPE calculated as 0.0001 for best ANN model, which indicate superiority of this model over the prediction models. Based on the literature, there was no study on energy and economical analysis and modeling of output energy for maize productions in Iran. Therefore, the main objective of this study was to compare the energy use and economic efficiencies and prediction of output energy for maize production in Khuzestan province of Iran.

Materials and Methods

Sampling design: This study was conducted in summer 2015 in Shooshtar County (32 30' N, 48 20' E), south of Iran. Shooshtar is one of the important maize production areas in the south part of Iran in Khuzestan province that maize is grown as second crop. The data used in this study were collected from 40 farms using a face to face questionnaire in the studied area. The Cronbach method was applied to estimate the reliability of a psychometric test for samples [19]. The simple random sampling method was used to determine the survey volume, described by Rafiee et al., (2010) [20]:

$$n = \frac{N(s \times t)^2}{(N-1)d^2 + (s \times t)^2} \qquad (1)$$

where n is the required sample size; s is the standard deviation; t is the value at 95% confidence limit (1.96); N is the number of holding in target population and d is the acceptable error (permissible error 5%).

Energy Analysis: A standard procedure was used to convert each agricultural input and output into energy equivalents (Table 1). Inputs in maize production included: human labor, machinery, diesel fuel, chemical fertilizer, chemicals, Water for irrigation and seed. The output was considered maize. The energy equivalents given in Table 1 were used to calculate the input amounts.

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

Inputs (unit)	Unit	Energy equivalent (MJ unit^{-1})	Reference
A. Inputs			
1. Human labor	h	1.96	[21]
2. Machinery	h	62.70	[22]
3. Diesel fuel	L	56.31	[23]
4. Total fertilizers	kg		
(a) Nitrogen		66.14	[13]
(b) Phosphate		12.44	[24]
(c) Potassium		11.15	[25]
(d) Farmyard manure	kg	0.3	[26]
5. Chemicals	kg		
(a) Pesticide		199	[26]
(b) Fungicide		92	[3]
6. Water for irrigation	m^3	1.02	[27]
7. seed	kg	14.7	[3]
B. Output			
Maize	kg	14.7	[3]

The energetic efficiency of the agricultural system can be evaluated by the relation between energy inputs and output [28]. Based on the energy equivalents of inputs and outputs, the indices of energy use efficiency, energy productivity, specific energy and net energy were calculated using the following Eqs [20]:

Energy use efficiency = (Energy output (MJ ha^{-1})) / (Energy input (MJ ha^{-1})) (2)

Energy productivity = (maize output (kg ha^{-1})) / (Energy input(MJha^{-1})) (3)

Specific energy = (Energy input (MJ ha^{-1})) / (maizeoutput(kgha^{-1})) (4)

Net energy = (Energy output (MJ ha^{-1})) - (Energy input(MJha^{-1})) (5)

Energy use efficiency is defined as the ratio between the caloric heat of the output products and the total sequestered energy in the production factors. Energy productivity is the amount of a product obtained per unit of input energy. Energy output and net energy are crucial parameters when the availability of arable land is the limiting factor for plant production [29]. The energy inputs were divided into direct and indirect and renewable and non-renewable energy forms [30]. Direct energy consisted of human labour, diesel fuel; whereas, indirect energy included machinery, chemical fertilizers, farmyard manure, biocides and seeds. On the other hand, renewable energy consists of human labour, farmyard manure and seeds and non-renewable energy includes machinery, diesel fuel, chemical fertilizers, biocides and electricity.

Economic analysis: In the last part of this study the economic analysis of maize production was investigated. So the following indicators were used [31]:

Total production value = maize yield (kg ha^{-1}) × maize price ($kg^{-1}) (6)

Gross return = Total production value ($ ha^{-1}) – Variable cost of production ($h^{-1}) (7)

Net return = Total production value ($ ha^{-1}) – Total production costs ($ha^{-1}) (8)

Benefit - Cost ratio = Total production value ($ ha^{-1}) / Total production costs ($ha^{-1}) (9)

Productivity = maize yield (kg ha^{-1}) / Total production costs ($ha^{-1}) (10)

All estimations were carried out using the Microsoft Excel spreadsheet program.

Artificial neural networks: Artificial neural networks are computational models that have been simulation from real biological networks and composed of nerve cells [32]. Each network trained with examples and the neural network be trained can predict the proportional output with the new set of data [33]. Multi-layer neural networks based on the back propagation algorithm is the most common artificial neural networks that are composed from several layers of simple processing elements that called neurons [34]. The overall structure of artificial neural network is composed of a layer of input neurons and a layer of output neurons and one or more hidden layers [35]. Input and output layers are connected by a hidden layer. One of the problems that may occur when the neural network training is over training. This means that during training the error reaches to acceptable level but when evaluating, the network error is more than the training data error [36]. There are two ways for avoid of over-training: stop training quickly and select the minimum number of neurons in the hidden layer as possible [37]. In this research for solve this problem was used of second method. For learning network, data were divided into three parts randomly, 70% of the data for training, 15% for testing and 15% for validation were divided. The learning function was sigmoid and learning algorithm was selected multi-layer neural networks based on the back propagation too. For making neural networks of required was used from the MATLAB version 7.1 (R2013a). The number of neurons from 1 to 20 and the number of hidden layers from 1 to 2 layer changed and the best model was extracted, finally. The amount of energy equivalent to fossil fuels, labor electricity, machinery and equipment and feed were as input parameters and the output energy of maize was considered as output parameters.

To determine the best model derived from between models made with artificial neural networks were used from various statistical indicators, such as RMSE and R2. The following is provided equations related to the statistical indicators [22].

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2} \right) \qquad (11)$$

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

$$\mathrm{MSE} = \sqrt{\frac{1}{\mathrm{n}} \sum_{i}^{n} \left(t_i - z_i\right)^2} \qquad (12)$$

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.

Results and Discussion

Table 2: Amounts of energy inputs and output for maize production in shooshtar, Iran

Inputs (unit)	Total energy (MJ ha^{-1})	Percentages (%)
A. Inputs		
1. Human labor (h)	224	0.56
2. Machinery (h)	1850.42	4.70
3. Diesel fuel (L)	13761.98	35.01
4. Total fertilizers (kg)		
(a) Nitrogen	15261.92	38.83
(b) Phosphate	1614.36	4.10
5.seed	3030.28	7.70
6. Water for irrigation	3560.95	9.06
The total energy input (MJ)	39303.91	100
B. Output		
1.maize (kg)	58077.41	

Analysis of input-output energy use in maize production: The inputs used in maize production, Energy quantity per unit area, total energy equivalent and the percentage of each input are shown in Table 2. The results illustrated that Nitrogen Fertilizer with 15261.92 MJ ha^{-1} and 38.83% of total inputs had the highest share in maize production. After that diesel fuel with 13761.98 MJ ha^{-1} and 35.01% of total inputs had the highest share.

The total energy input for various processes in maize production was calculated to be 39303.91 MJ ha^{-1} (Table 2). Human labor with 224 MJ ha^{-1} and 0.56% had the least share. Hamedani et al., (2011) concluded that the total energy input for grape production in Hamedan province of Iran was found to be 45213.66 MJ ha^{-1} [27]. Water for irrigation with 229.59 MJ ha^{-1} and 1.1% of total inputs had a little share in the production. Also, they reported that the grape production consumed 550.4 MJ ha^{-1} of chemicals, (1.2% of total inputs). The average yield of maize production was obtained to be 58077.41 kg ha^{-1} (Table 2).
Accordingly, the inputs were classified into direct and indirect and also renewable and non-renewable energy as shown in Table 3. The total energy input necessary for maize production was 39303.91 MJ/ha. Out of all 55.35% of the total energy, input use in maize production was in the form of indirect energy. The remaining part of energy input use (35.58%) was in the form of direct energy. On the other hand the research results indicate that the total energy input used in maize production systems was mainly dependent on non-renewable energy forms (Table 3). As can be seen from the table, on an average, the non-renewable form of energy input was 82.66% in maize production systems of the total energy input while the 8.27% of input energy was renewable energy resource. The high rate of non-renewable and direct energy inputs indicates an intensive use of chemical fertilizer and diesel fuel consumption in these agroecosystems.

Table 3: Total energy input in the form of direct, indirect, renewable and Non-renewable for maize production ($MJha^{-1}$)

Items	Unit	Quantity	Percentages (%)
Total energy consumption	MJ ha^{-1}	39303.91	100
Direct energy	MJ ha^{-1}	13985.98	35.58
Indirect energy	MJ ha^{-1}	21756.98	55.35
Renewable energy	MJ ha^{-1}	3254.28	8.27
Non-renewable energy	MJ ha^{-1}	32488.68	82.66

Results of energy indicators for maize production systems are shown in Table 4. Accordingly energy efficiency (output-input ratio) was 1.47. Lower energy use efficiency in maize production systems is due to higher energy inputs in these systems for example N fertilizer consumed. Thus indicator was reported 2.8 for wheat production systems in Turkey [38] and 25.75 for sugar beet in turkey [9]. Energy productivity (maize yield per energy input) and specific energy (input energy per grain yield) in maize production was 0.10 $KgMJ^{-1}$ and 9.94 $MJKg^{-1}$ respectively. This means that produced maize grain yield per input energy unit was 0.10$kgMJ^{-1}$, or in the other word, in maize production systems, 9.94MJ energy used for production one kg of grain yield. Also, System net energy (output minus input) was calculated as 18773.5 $MJha^{-1}$.

Table 4: Indicators of energy use in maize production

Energy use efficiency	-	1.47
Energy productivity	kg MJ^{-1}	0.1
Specific energy	MJ kg^{-1}	9.94
Net energy gain	MJ ha^{-1}	18773.5

Economical analysis of maize production: In table 5, the economical analysis of maize production comparatively presented. The total production values, gross and net returns and benefit to cost ratio were calculated. The fixed and variable expenditures included in the cost of production were calculated in detail. The variable cost of production was found to be and 450.49 \$ ha^{-1}. The total cost of production in farms was found to 1380.56 \$ ha^{-1}.On the other hand, the fixed costs of production in farms was found to be 529.14 \$ ha^{-1}. The net return for maize production calculated as 1108.44 \$ ha^{-1}. Also, benefit to cost ratio, respectively, (1.80 vs. 2.86). Mousavi-Avval et al., (2011) concluded that canola production in medium farms showed the highest energy use efficiency as 3.43, the energy productivity was found to be 0.14, also, specific energy was 7.29 Kg ha^{-1} [13] The total cost of production, the fixed costs of production, the net return for canola production, benefit to cost ratio in medium farms were found to be 907.6 \$ ha^{-1}, 536.57 \$ ha^{-1}, 532.81 \$ ha^{-1} and 1.29, respectively.

Table 5: Economical analysis of maize production in shooshtar, Iran.

Yield (Kg ha^{-1})	3950.84
Sale price ($ kg^{-1})	0.63
Total production value ($ ha^{-1})	2489
Variable cost of production ($ ha^{-1})	450.49
Fixed cost of production ($ ha^{-1})	592.14
Total cost of production ($ ha^{-1})	1380.56
Total cost of production ($ kg-1)	0.49
Gross return ($ ha^{-1})	2038.51
Net return ($ ha^{-1})	1108.44
Benefit to cost ratio	1.80
Productivity ($ kg^{-1})	2.86

Evaluation of artificial neural network: For find the best model with the maximum R2 and minimum error, various networks with different changes were made and have been examined. These changes include the change in the number of hidden layers change in the number of neurons and changes in learning parameters and network architecture. The selected artificial neural network has been structured with an input layer with 5 neurons, a hidden layer with 14 neurons and an output layer with 1 neurons (5-14-1), eventually. The plots the output from the software have been shown in Fig. 1

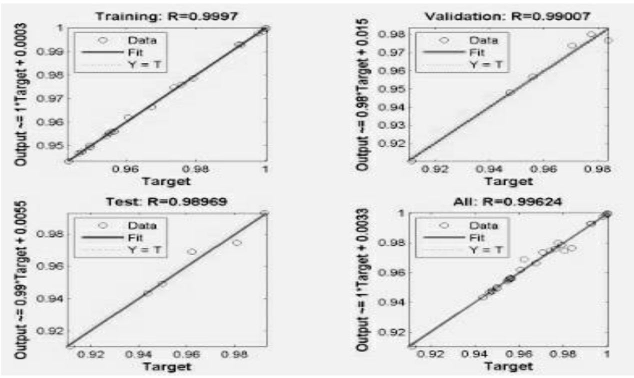

Figure 1: The most appropriate topology for communication between actual data and predicted data with the selected artificial neural networks.

Table 6: ANN models of alfalfa prediction for different arrangement

R^2 test	R^2 train	RMSE	Hidden layers	Neurons of hidden
0.3731	0.6807	0.2853	1	2
0.6285	0.8539	0.1032	1	4
0.4558	0.7285	0.1735	2	2
0.4252	0.5840	0.1930	2	4
0.8357	0.8958	0.0120	1	6
0.6776	0.7292	0.162	1	8
0.4949	0.5183	0.1864	2	6
0.6189	0.7335	0.1369	2	8
0.8456	0.8629	0.0570	1	10
0.9000	0.9040	0.0175	1	12
0.9539	0.9580	0.0057	2	10
0.9644	0.9687	0.0045	2	12
0.9793	0.9994	0.0026	1	14

Charts show that R obtained for modeling with the chosen network for all data and data that have been used for network training is 0.99 that indicates the high ensure of the network was established. The results indicated, structure with one hidden layer and fewer neurons shows better results. Statistical indicators were computed for modeling with artificial neural networks for the amount of energy output has been shown in Table 6; that the modeling with neural network selected for predict the amount of energy output is acceptable amount according to the amount of R2. The results this study and other research that have been done related to the modeling of artificial neural networks in the process production of crops has shown that the modeling by artificial neural networks for these products is ideal. For example, for predict the yield performance of hemp, the structure with input layer (six neurons), two hidden layers (9 and 5 neurons) and an output layer (a neuron) was used that had good results [39].

Conclusion

In this study the energy use efficiency and benefit to cost ratio of maize production in farms was examined. Data used in this study were obtained from 30 randomly selected maize farms in Shooshtar, Iran. The following conclusions are drawn:

1. Total energy input and output for maize production were found to be 39303.91 and 58077.41 MJ ha^{-1}, respectively.
2. The energy use efficiency, energy productivity and specific energy were found to be 1.47, 0.1 and 9.94, respectively.
3. The Variable cost of production and Fixed cost of production were found to be 450.49 and 592.14 (\$ ha^{-1}), respectively.
4. The Gross return, Net return, Benefit to cost ratio, Productivity were found to be 2038.51, 1108.44 (\$$ha^{-1}$) and 1.80 and 2.86 (\$$kg^{-1}$), respectively.
5. The ANN model with (5-14-1) structure was the best model energy output in maize.

Acknowledgment

The financial support provided by the Shoushtar Branch, Islamic Azad University, Iran, is duly acknowledged.

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