INNSPUB

International Journal of Agronomy and Agricultural Research (IJAAR)
ISSN: 2223-7054 (Print) 2225-3610 (Online)
http://www.innspub.net
Vol. 4, No. 5, p. 57-64, 2014

RESEARCH PAPER OPEN ACCESS

Prediction of yield and economic indices for tangerine production using artificial neural networks based on energy consumption

Ashkan Nabavi-Pelesaraei*, Farhad Fatehi, Asghar Mahmoudi

Department of Agricultural Machinery Engineering, Faculty of Agriculture, University of Tabriz, Tabriz, Iran

Article published on May 15, 2014

Key words: Artificial neural network, economic indices, energy, modeling, tangerine yield.

Abstract

Determination of suitable model for forecasting of yield and economic indices of tangerine production in Guilan province of Iran using artificial neural network (ANN) was the main aim of this study. For this purpose, the energy consumption for three groups size of tangerine orchards were found from 60 questionnaires. The results revealed the average total energy use and yield of tangerine production were 27873 MJ ha^{-1} and 25740 kg ha^{-1}, respectively. In the next step, the economic indices were calculated for tangerine orchards. Accordingly, benefit to cost ratio, productivity, net return and energy intensiveness were calculated as 1.37, 3.42 kg $\$^{-1}$, 2777.82 \$ ha^{-1}, 2.71 \$ ha^{-1}, respectively. In this study, a back propagation algorithm was used for training of ANN model and Levenberg-Marquardt was learning algorithm. The best topology had the 10-8-5 structure. Moreover, the R^2 of best structure was found 0.971, 0.954, 0.983, 0.991 and 0.973 for tangerine yield, benefit to cost ratio, productivity, net return and energy intensiveness, respectively. In the last section of this research, sensitivity analysis was done and results illustrated the highest sensitivity rate of tangerine yield, the benefit to cost ratio, productivity, net return and energy intensiveness was belonged to farmyard manure, insecticide, insecticide, phosphate and diesel fuel, respectively.

* **Corresponding Author:** Ashkan Nabavi-Pelesaraei ✉ ashkan.nabavi@yahoo.com

Introduction

Tangerine is one of the most popular varieties of the citrus fruit commonly known as the orange. The tangerine is actually an offshoot of the mandarin family of oranges (Penjor *et al.,* 2013). Energy is a fundamental part of economic development because it provides essential services that maintain economic activity and the quality of human life. The vital role of precious energy in the development of key sectors of economic importance such as industry, transport, and agriculture has motivated many researchers to focus on energy management (Unakitan *et al.,* 2010). In order to maximize the efficiency of new agricultural technology to farms in a target region, the farming system of the region should be first characterized, especially to identify possible resource constraints and to capture the diversity of farming systems (Zangeneh *et al.,* 2010). In other hand, economic analysis of agricultural activity is very important for both of consumer and producer in agricultural and horticultural products. In general, increases in the agricultural production on a sustainable basis and at a competitive cost are vital to improve the farmer's economic condition (Mohammadi and Omid, 2010). The economics of tangerine production depend on numerous factors, but most important is a general economic policy. Other factors include the choice of production technology, the organization and the productivity of labor, and the extent of the exploitation of the productive factors. Neural networks are a wide class of flexible nonlinear regression and discriminate modes, data reduction models, and nonlinear dynamical systems. They consist of an often large number of "neurons," i.e. simple linear or nonlinear computing elements, interconnected in often complex ways and often organized into layers (Warren, 1994). Artificial neural network (ANN) models can be used to overcome the non-linearity problem. The ANN is a form of artificial intelligence that was inspired by the studies of the human neuronal and has been used to analyze biophysical data. ANN model has the ability to auto-analyze the relationships between multi-source inputs (including combinations of qualitative and quantitative data) by self-learning, and produce results without hypothesis (Zhao *et al.,* 2009). Interest in the use of ANN for the modeling of energy consumption and economic indices in agricultural processes has increased in recent years. Safa and Samarasinghe (2011) used ANNs for determining and modeling of energy consumption in wheat production. They compared ANNs with multiple linear regression (MLR) and found that ANNs can predict energy consumption better than MLR. Khoshnevisan *et al.* (2013a) modeled the energy use and greenhouse gas emissions for wheat production based on energy inputs using ANN. Nabavi-Pelesaraei *et al.* (2013a) examined the ANN model of energy consumption for eggplant production in Guilan province of Iran. In another study, Khoshnevisan *et al.* (2014) applied ANN for prediction of potato yield based on energy inputs. Zangeneh *et al.* (2011) compared parametric model and ANN for assessing economical productivity, total costs of production and benefit to cost ratio of potato crop. Farjam *et al.* (2014) determined the energy use pattern and several economic indices for corn seed and grain corn production in Ardabil province, Iran. Then, they determined the best topology for prediction of economic indices of corn seed and grain corn.

Based on the literature, the aims of this study were determining of energy inputs and economic indices and developed the ANN model and calculation of the best topology for prediction of each of them in tangerine production in Guilan province of Iran.

Materials and methods

Data collection and case study

This study was carried out in the orchards located in Guilan province, Iran. This province is located in the north of Iran, within $36^{\circ}\ 34'$ and $38^{\circ}\ 27'$ north latitude and $48^{\circ}\ 53'$ and $50^{\circ}\ 34'$ east longitude (Nabavi-Pelesaraei *et al.,* 2014). Langroud city with 60% of total citrus production had the special place in producing tangerine in of Guilan province (Anon, 2013). Data were collected from 60 orchardists by using a face-to-face questionnaire performed in the production year 2012/2013. Average orchard size was about 1 ha in the area studied while the size of orchards varied between

0.33 ha and 12 ha. From the villages in the area studied, orchards were selected by using a stratified sample randomly. The sample size was calculated using the Cochran method (Kizilaslan, 2009).

Energy consumption

The only output energy source was tangerine fruit; while the input energy sources for tangerine production were human labor, machinery, diesel fuel, chemical fertilizers (nitrogen, phosphorus and potassium), farmyard manure, pesticides (insecticide and fungicide) and electricity in this region. The energy values were calculated by transforming data using energy equivalents shown in Table 1. For this purpose, the quantity of each energy input was multiplied by corresponding coefficients; which are given in Table 1. Also, calculating machinery energy related to their manufacturing or hours of use was found to be significant and was considered in the analysis.

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	(Mobtaker *et al.,* 2012)
2. Machinery	h	62.70	(Qasemi-Kordkheili and Nabavi-Pelesaraei, 2014)
3. Diesel fuel	L	56.31	(Mobtaker *et al.,* 2010)
4. Chemical fertilizers	kg		
(a) Nitrogen		66.14	(Nabavi-Pelesaraei *et al.,* 2013a)
(b) Phosphate(P_2O_5)		12.44	(Rafiee *et al.,* 2010)
(c) Potassium (K_2O)		11.15	(Unakitan *et al.,* 2010)
5. Farmyard manure	kg		
6. Pesticides	kg		
(a) Insecticide		199	(Ozkan *et al.,* 2004)
(b) Fungicide		92	(Ozkan *et al.,* 2004)
7. Electricity	kWh	5.9	(Kitani, 1999)
B. Output			
Tangerine	kg	5.9	(Kitani, 1999)

The tangerine orchards were classified into small orchards (<1 hectare), medium orchards (between one and three hectares) and large orchards (>3 hectares) in the studied area. Also, the analysis of variance (ANOVA) was used for comparison of the three groups. Furthermore, the means comparison was done by Duncan mean test for the three groups.

Economic indices

Economic indicators can be computed. The economic benefit analysis focuses on the total cost of production, gross value of production, energy intensiveness, and net return.

Benefit to cost ratio, productivity, net return and energy intensiveness were calculated by Eqs. (1)-(5) (Mandal *et al.,* 2002; Mohammadi *et al.,* 2008; Mohammadshirazi *et al.,* 2012; Tabatabaie *et al.,* 2013):

$$\text{Gross production value} = \text{T}\mathit{angerine}\ \text{yield}\,(\text{kg ha}^{-1}) \times \text{T}\mathit{angerine}\ \text{price}\,(\$\ \text{kg}^{-1}) \tag{1}$$

$$\text{Benefit to cost ratio} = \frac{\text{Gross production value (\$ ha}^{-1}\text{)}}{\text{Total production cost (\$ ha}^{-1}\text{)}} \tag{2}$$

$$\text{Productivity} = \frac{\text{Yield (kg ha}^{-1}\text{)}}{\text{Total production cost (\$ ha}^{-1}\text{)}} \tag{3}$$

$$\text{Net return} = Gross\ \text{production value (\$ ha}^{-1}\text{)} - Total\ \text{production cost (\$ ha}^{-1}\text{)} \tag{4}$$

$$\text{Energy intensiveness} = \frac{\text{Energy input (MJ ha}^{-1}\text{)}}{\text{Total production cost (\$ ha}^{-1}\text{)}} \tag{5}$$

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 (Nabavi-Pelesaraei *et al.,* 2013b).

ANN modeling

Since the middle of 1980s, artificial neural network (ANN) as a branch of artificial intelligent (AI) has been drawing engineers' and scientists' attention and it has been widely applied to energy and environmental modeling. The great benefit of ANNs over statistical methods is that they require no assumptions about the form of a fitting function as well as the simplicity of application and robustness of the results. Multilayered, back propagation, fully connected network of perceptions is the most common ANN and is composed of three layers of neurons consists of an input layer, hidden layer(s) and an out-put layer. In general, the structure of a back propagation network typically comprised of three layers including input, hidden and output layers (Khoshnevisan *et al.,* 2013b). Input data are first collected in the input layer, and then sent to different processing units (neuron), which constitute the hidden layer of the networks (Rahimi-Ajdadi and Abbaspour-Gilandeh). Also, the learning algorithm of ANN model was Levenberg-Marquardt in this study.

The input weight matrixes are made up from all the links between input layers and hidden layers and the output weight matrix comprises all the links between the hidden layers and the output 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. (6) (Zhao *et al.,* 2009):

$$O = f\left(T + \sum w_i x_i\right) \tag{6}$$

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

The error was calculated at the end of training and testing processes based on the differences between targeted and calculated outputs. The back-propagation algorithm minimizes an error function defined by the average of the sum square difference between the output of each neuron in the output layer and the desired output.

The error function can be expressed as (Khoshnevisan *et al.,* 2013a):

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

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

Mean square error (MSE) is very applicable to compare different models; it illustrates the network's ability to predict the accurate output. The MSE can be written as (Safa and Samarasinghe, 2011):

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

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.

Mean absolute percentage error (MAPE) between the predicted and actual values and coefficient of determination (R^2) were calculated using the following equations (Khoshnevisan *et al.,* 2013b):

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

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

Where 't_i' and 'z_i' are the predicted and actual output for the i^{th} orchardist, respectively.

Basic information on energy inputs and economic indices of tangerine production was entered into Excel 2010 spreadsheets and the Matlab 7.2 (R2012a) software package.

Results and discussion

Analysis of input energy use and yield of tangerine production

Table 2 shows the quantity of input energy and output yield productions in the horticultural tangerine production stage for three tangerine orchard sizes. In the surveyed region, the average total energy used in the orchard operations during tangerine production and yield was 27873.00 MJ ha^{-1} and 25740.00 kg ha^{-1}, respectively. Large orchards had the highest total energy inputs and yield among all orchards. ANOVA and means test results revealed differences between energy used in three orchard sizes in tangerine production wasn't significant; Vise versa, the difference between yield was significant. In other words, the more yield can be achieved by lower energy consumption. In all of orchards, the energy consumption of nitrogen (with average about 13686 MJ ha^{-1}) had the highest. Because the rainy weather in Guilan province makes the irregular leaching of chemical fertilizers. Also, cheap fertilizers were the one of the main reason of inappropriate consumption of nitrogen in the studied area. So, it's suggested the nitrogen fertilizer should be reduced in unit of orchard by applying appropriate horticultural system and replacing farmyard manure instead of chemical fertilizers (especially nitrogen) in Guilan province, Iran.

Table 2. Amounts of energy inputs and yield of tangerine production based on different orchard size levels.

Items	Units	Orchard size groups (ha)			Average (unit)
		Small (<1)	**Medium (1-3)**	**Large (>3)**	
A. Inputs					
1. Human labor	MJ ha^{-1}	2981.57^a	3617.89^b	3601.44^b	3551.51
2. Machinery	MJ ha^{-1}	881.68^a	1271.05^b	1333.38^c	1242.50
3. Diesel fuel	MJ ha^{-1}	1001.23^a	1489.89^b	1473.47^b	1438.29
4. Chemical fertilizers	MJ ha^{-1}				
(a) Nitrogen		11776.13^a	13365.72^{ab}	16243.65^b	13686.42
(b) Phosphate (P_2O_5)		754.65^a	1643.41^{ab}	1819.38^b	1584.01
(c) Potassium (K_2O)		3125.93^a	3829.15^b	3623.96^c	3724.63
5. Farmyard manure	MJ ha^{-1}	456.00^a	503.74^b	475.95^b	494.34
6. Pesticides	MJ ha^{-1}				
(a) Insecticide		113.13^a	200.73^{ab}	239.51^b	198.43
(b) Fungicide		131.40^a	317.64^b	340.05^c	302.75
7. Electricity	MJ ha^{-1}	1610.06^a	1648.11^b	1683.00^c	1650.12
The total energy input	MJ ha^{-1}	22831.78^a	27877.53^a	30833.80^a	27873.00
B. Output					
Tangerine	kg ha^{-1}	18893.00^a	26000.00^b	28704.00^c	25740.00

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

Mohammadshirazi *et al.* (2012) calculated the energy inputs for tangerine production about 35370 MJ ha^{-1}. In some related studies total energy input has been reported at 32 to 40 GJ ha^{-1} for dryland grapes (Hertz, 1998), 62.98 GJ ha^{-1} for lemons (Strapatsa *et al.,* 2006), 81.36 GJ ha^{-1} for apples (Rafiee *et al.,* 2010), 30.28 GJ ha^{-1} for kiwifruit production (Mohammadi *et al.,* 2010), 45.21 GJ ha^{-1} for grapes (Hamedani *et al.*, 2011), 172.61 GJ ha^{-1} for pears (Tabatabaie *et al.,* 2013) and 25.58 GJ ha^{-1} for orange production (Nabavi-Pelesaraei *et al.,* 2014).

Economics indices results of tangerine production

The results of economic indices are tabulated in Table 3. The results revealed the gross production value was calculated 10296.00 \$ ha^{-1}. This index showed the average total income of tangerine orchardists (with regardless of cost). Variable and fixed production cost were found about 5170 and 2347.91 \$ ha^{-1}, respectively. Obviously, total production was 7518.18 \$ ha^{-1}. As can be seen in Table 3, the benefit to cost ratio, productivity, net return and energy intensiveness were 1.37, 3.42 kg \$$^{-1}$, 2777.82 \$ ha^{-1}, 2.71 \$ ha^{-1}, respectively.

Table 3. Economic indices results of tangerine production in Guilan province, Iran.

Cost and return components	Unit	Value
Yield	kg ha^{-1}	25740.00
Tangerine price	\$ kg^{-1}	0.4
Gross production value	\$ ha^{-1}	10296.00
Variable production cost	\$ ha^{-1}	5170.27
Fixed production cost	\$ ha^{-1}	2347.91
Total production cost	\$ ha^{-1}	7518.18
Benefit to cost ratio	-	1.37
Productivity	kg \$$^{-1}$	3.42
Net Return	\$ ha^{-1}	2777.82
Energy intensiveness	\$ ha^{-1}	2.71

Mohammadi *et al.* (2010) reported the benefit to cost ratio of kiwifruit production was 1.94. In another study, the benefit to cost ratio, energy intensiveness and productivity of tangerine production were calculated as 1.62, 7.36 and 5.19 kg \$$^{-1}$ in Mazandaran province of Iran, respectively (Mohammadshirazi *et al.,* 2012).

Evaluation and analysis of the model

Various ANNs were trained for modeling of tangerine yield and economic indices in this research. These networks contained one input layer with ten inputs, one and two hidden layers and one output layer with five outputs based on back propagation algorithm under Levenberg-Marquardt learning algorithm. The results indicated one hidden layer with 10-8-5 structure had the best topology, which is shown in Fig 1. The results of the best topology are given in Table 4. Accordingly, the determination of coefficient was computed as 0.971, 0.954, 0.983, 0.991 and 0.973 for tangerine yield, benefit to cost ratio, productivity, net return and energy intensiveness, respectively. As can be seen in Table 4, the lowest RMSE and MAPE was found for all outputs.

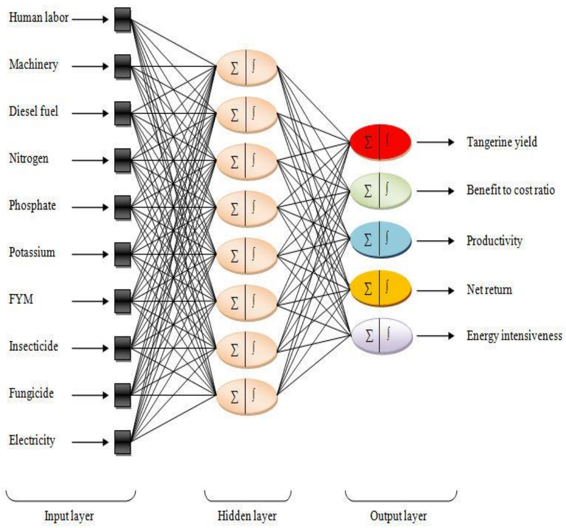

Fig. 1. Schematic diagram of the best topology with 10-8-5 structure.

Table 4. The best result of different arrangement of models.

Item	Tangerine yield	Benefit to cost ratio	Produ-ctivity	Net return	Energy inten-siveness
R^2	0.971	0.954	0.983	0.991	0.973
RMSE	0.043	0.032	0.048	0.059	0.051
MAPE	0.131	0.073	0.094	0.119	0.062

Taki *et al.* (2012) predicted corn silage production using an ANN model, including an input layer (with eight neurons), two hidden layers (with 5 neurons in each layer) and an output layer (with one neuron). In another study, two ANN models with 8-15-13-1 and 8-13-15-1 structures were developed to model benefit to cost ratio and total cost production of potato production (Zangeneh *et al.,* 2011). Nabavi-Pelesaraei *et al.* (2013a) developed an ANN model with 12-9-9-2 structure for eggplant production and greenhouse gas emissions in Guilan province of Iran. Moreover, Farjam *et al.* (2014) reported the best multilayer perceptron network models for predicting economic indices in seed and grain corn production had 6-6-10-4 and 6-4-8-4 topologies, respectively.

Sensitivity analysis

A technique used to determine how different values of an independent variable will impact a particular dependent variable under a given set of assumptions. This technique is used within specific boundaries that will depend on one or more input variables, such as the effect that changes in energy input rates will have on a yield in agricultural activity. In this study, the main aim of applying sensitivity analysis by ANN was determination of the effect of each energy input on tangerine yield and economic indices. Fig 2 displays the results of sensitivity analysis in this study. Accordingly, the highest sensitivity rate of tangerine yield, benefit to cost ratio, productivity, net return and energy intensiveness was belonged to farmyard manure, insecticide, insecticide, phosphate and diesel fuel, respectively.

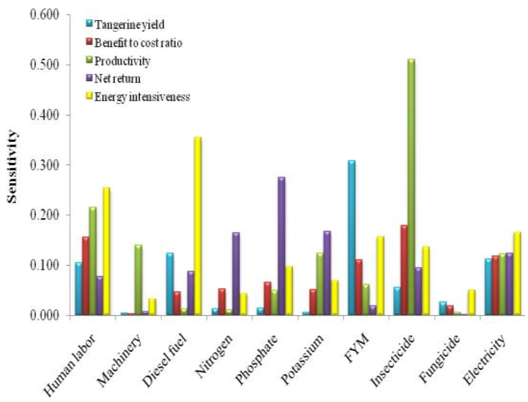

Fig. 2. Sensitivity analysis of various input energies on yield and economic indices of tangerine production in Guilan province, Iran.

Conclusions

In this study, in order for forecasting of yield and economic indices of tangerine production in the Langroud city of Guilan province of Iran, ANN modeling was used with respect to energy inputs in three orchard sizes in tangerine production. Also, sensitivity analysis was done for determination of the energy inputs effect in outputs.

Based on the results of the study the following conclusions are drawn:

1- The average of total energy used and yield of tangerine production was 27873 MJ ha^{-1} and 25740 kg ha^{-1}, respectively. Large orchards had the highest energy consumption and tangerine yield among three groups and the most consumer of energy was electricity among all inputs for in among for all three groups.

2- With respect to economic indices analysis, benefit to cost ratio, productivity, net return and energy intensiveness were calculated as 1.37, 3.42 kg $\$^{-1}$, 2777.82 \$ ha^{-1}, 2.71 \$ ha^{-1}, respectively.

3- The results of back propagation algorithm under Levenberg-Marquardt learning algorithm revealed the ANN model with 10-8-5 structure had been the best model for prediction of yield and economic indices in the studied area. The highest R^2 and lowest RMSE and MAPE was found from best structure for all five outputs.

Farmyard manure, insecticide, insecticide, phosphate and diesel fuel had the most sensitive in tangerine yield, benefit to cost ratio, productivity, net return and energy intensiveness among all inputs, respectively.

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 efforts to help me revise the study.

References

Anonymous. 2013. Annual Agricultural Statistics. Ministry of Jihad-e-Agriculture of Iran. http://www .maj.ir, [in Persian].

Farjam A, Omid M, Akram A, Niari ZF. 2014. A neural network based modeling of energy inputs for predicting economic indices in seed and grain corn production. Elixir Agriculture **66,** 20478-20481.

Hamedani S.R, Keyhani A, Alimardani R. 2011. Energy use patterns and econometric models of grape production in Hamadan province of Iran. Energy **36,** 6345-6351.

Hertz E. Energy utilization in fruit production in Chile. Agricultural Mechanization in Asia, Africa, and Latin America **29**(2), 17-20.

Khoshnevisan B, Rafiee S, Omid M, Mousazadeh H, Rajaeifar MA. 2014. Application of artificial neural networks for prediction of output energy and GHG emissions in potato production in Iran. Agricultural Systems **123,** 120-127.

Khoshnevisan B, Rafiee S, Omid M, Yousefi M, Movahedi M. 2013a. Modeling of energy consumption and GHG (greenhouse gas) emissions in wheat production in Esfahan province of Iran using artificial neural networks. Energy **52,** 333-338.

Khoshnevisan B, Rafiee S, Omid M, Mousazadeh H. 2013b. Environmental impact assessment of open field and greenhouse strawberry production. European Journal of Agronomy **50,** 29-37.

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

Kizilaslan H. 2009. Input-output energy analysis of cherries production in Tokat Province of Turkey. Applied Energy **86,** 1354-1358.

Mandal KG, Saha KP, Gosh PL, Hati KM, Bandyopadhyay KK. 2002. Bioenergy and economic analyses of soybean-based crop production systems in central India. Biomass Bioenergy **23,** 337-345.

Mobtaker HG, Akram A, Keyhani A. 2012. Energy use and sensitivity analysis of energy inputs for alfalfa production in Iran. Energy for Sustainable Development **16,** 84-89.

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.

Mohammadi A, Omid M. 2010. Economical analysis and relation between energy inputs and yield of greenhouse cucumber production in Iran. Applied Energy **87,** 191-196.

Mohammadi A, Rafiee S, Mohtasebi S.S, Mousavi-Avval SH, Rafiee H. 2010. Energy inputs – yield relationship and cost analysis of kiwifruit production in Iran. Renewable Energy **35,** 1071-1075.

Mohammadi A, Tabatabaeefar A, Shahan S, Rafiee S, Keyhani A. 2008. Energy use and economical analysis of potato production in Iran a case study: Ardabil Province. Energy Conversion and Management **49,** 3566-3570.

Mohammadshirazi A, Akram A, Rafiee S, Mousavi-Avval SH, Bagheri Kalhor E. 2012. An analysis of energy use and relation between energy inputs and yield in tangerine production. Renewable and Sustainable Energy Reviews **16,** 4515-4521.

Nabavi-Pelesaraei A, Abdi R, Rafiee S, Mobtaker HG. 2014. Optimization of energy required and greenhouse gas emissions analysis for orange producers using data envelopment analysis approach. Journal of Cleaner Production **65,** 311-317.

Nabavi-Pelesaraei A, Shaker-Koohi S, Dehpour M.B. 2013a. Modeling and optimization of energy inputs and greenhouse gas emissions for eggplant production using artificial neural network and multi-objective genetic algorithm. International Journal of Advanced Biological and Biomedical Research **1**(11), 1478-1489.

Nabavi-Pelesaraei A, Sadeghzadeh A, Payman MH, Mobtaker HG. 2013b. Energy flow modeling, economic and sensitivity analysis of eggplant production in Guilan province of Iran. International Journal of Agriculture and Crop Sciences **5**(24), 3006-3015.

Ozkan B, Akcaoz H, Karadeniz F. 2004. Energy requirement and economic analysis of citrus production in Turkey. Energy Conversion and Management **45,** 1821-1830.

Penjor T, Yamamoto M, Uehara M, Ide M, Matsumoto N, Matsumoto R, Nagano Y. 2013. Phylogenetic relationships of citrus and its relatives based on matK Gene Sequences. Plos one **8**(4), 1-13.

Qasemi-Kordkheili P, Nabavi-Pelesaraei A. 2014. Optimization of energy required and potential of greenhouse gas emissions reductions for nectarine production using data envelopment analysis approach. International Journal of Energy and Environment **5**(2), 207-218.

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

Rahimi-Ajdadi F, Abbaspour-Gilandeh Y. 2011. Artificial Neural Network and stepwise multiple range regression methods for prediction of tractor fuel consumption. Measurement **44,** 2104-2111.

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.

Strapatsa AV, George D, Nanos A, Tsatsarelis Constantinos A. 2006. Energy flow for integrated apple production in Greece. Agriculture, Ecosystems and Environment **116,** 176-180.

Tabatabaie S.M.H, Rafiee S, Keyhani A, Heidari M.D. 2013. Energy use pattern and sensitivity analysis of energy inputs and input costs for pear production in Iran. Renewable Energy **51,** 7-12.

Taki M, Mahmoudi A, Mobtaker H.G, Rahbari H. 2012. Energy consumption and modeling of output energy with multilayer feed-forward neural network for corn silage in Iran. CIGR Journal **14**(4), 93-101.

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

Warren S. 1994. Neural networks and statistical models. Proceedings of the Nineteenth Annual SAS Users Group International Conference, April.

Zangeneh M, Omid M, Akram A. 2010. Assessment of machinery energy ratio in potato production by means of artificial neural network. African Journal of Agricultural Research **5**(10), 993-998.

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.