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Forecasting of Tea Yield Based on Energy Inputs using Artificial Neural Networks (A case study: Guilan province of Iran)

Farshad Soheili-Fard* and Seyed Babak Salvatian**
**Department of Biosystem Engineering, Faculty of Agriculture, University of Tabriz, Tabriz, IRAN.*
***Tea Research Institute, Lahijan, Guilan Province, IRAN.*

(Corresponding author: Farshad Soheili-Fard)
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ABSTRACT: The objective of this study was the exploring relation between energy inputs and tea yield using artificial neural network (ANN) in the Guilan province of Iran. For this purpose, the energy use pattern was determined by collection data from 30 tea farmers using face-to-face questionnaire method in the many village of studied region. The results indicated the total energy consumption and yield of tea production were 46144.04 MJ ha^{-1} and 8419.47 kg ha^{-1}, respectively. The highest share of energy consumption was belonged to nitrogen with 50.84%. In this study, the energy indices covering energy use efficiency, energy productivity, specific energy and net energy were calculated at 0.18, 0.23 kg MJ^{-1}, 4.38 MJ kg^{-1} and -37724.57 MJ ha^{-1}, respectively. Moreover, the share of energy forms including direct, indirect, renewable and non-renewable energies was found to be as 42.96%, 57.04%, 28.34% and 71.66%, respectively. For forecasting of tea yield based on energy inputs, ANN model developed by Back propagation algorithm in this study. The results illustrated the ANN model with 7-13-13-1 architecture had the best condition for predict of tea yield. With respect to ANN model, R2, RMSE and MAPE was computed as 0.968, 0.105 and 0.006, respectively. In the last section of this study, sensitivity analysis was applied by ANN for robustness of evaluated mode. The results disclosed the farmyard manure had the highest rate of sensitivity among all inputs.

Keywords: Artificial neural networks, Energy, Forecast, Model; Tea production.

INTRODUCTION

The tea plant, *Camellia sinensis* (L.) O. Kuntze, family Theaceae, is a small evergreen, perennial, cross-pollinated plant and grows naturally as tall as 15 m. However, under cultivated conditions, a bush height of 60-100 cm is maintained for harvesting the tender leaves (Soheili-Fard *et al.,* 2014). Energy has an influencing role in the development of key sectors of economic importance such as industry, transport and agriculture. This has motivated many researchers to focus their research on energy management. 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. Agriculture is both a producer and consumer of energy. It uses large quantities of locally available non-commercial energy, such as seed, manure and animate energy, as well as commercial energies, directly and indirectly, in the form of diesel, electricity, fertilizer, plant protection, chemical, irrigation water, machinery etc. Efficient use of these energies helps to achieve increased production and productivity and contributes to the profitability and competitiveness of agriculture sustainability in rural living. 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. However, more intensive energy use has brought some important human health and environment problems so efficient use of inputs has become important in terms of sustainable agricultural production (Taheri-Garavand *et al.,* 2010). The artificial neural network (ANN) modeling is of competent soft computing techniques that endeavor mimicking the human biological nervous system by interconnecting various artificial elements, so called as neurons. ANN has been a dynamic interest studying filed with ever-increasing application for modeling in diversity of science and engineering contexts.

The main reason for the acceptability and applicability of ANN is that the methodology is comparable to statistical modeling and ANNs could be dealt with as complementary effort or an alternative approach to fitting non-linear data. ANN, which explores the input-output relationships without any given explicit information on the processes, has been extensively applied for describing complex non-linear relationships within various scientific disciplines (Taghavifar and Mardani, 2015). In recent years many researcher used ANN method for modeling of energy consumption in agricultural and horticultural crop production. Rahman and Bala (2010) predicted jute production in Bangladesh using ANNs. In another study, Safa and Samarasinghe (2011) developed a neural network model to predict energy consumption of wheat production in New Zealand. They also compared ANNs with the multiple linear regression model (MLR) and found that ANNs can predict energy consumption better than MLR. Khoshnevisan *et al.* (2013) investigated on ANN model of energy use and greenhouse gas emissions of wheat production in Esfahan province, Iran. Soni *et al.* (2013) examined CO_2 emissions and energy use patterns in rain-fed agricultural production systems of northeast Thailand. Nabavi-Pelesaraei *et al.* (2013a) examined the ANN model for prediction of eggplant yield in north of Iran. In another study, the yield and greenhouse gas emissions of watermelon production calculated by Nabavi-Pelesaraei (2014a). Taghavifar and Mardani (2015) applied the ANN method for modeling of apple yield based on energy inputs.

With respect to above literature, the main purposes of this study was to evaluate of energy use pattern of tea production in Guilan province of Iran and applying this pattern in modeling of tea yield using ANN approach.

MATERIALS AND METHODS

A. Collection data and case study

This study follows our previous study which was conducted on modeling and relationship between CO_2 emitter inputs and yield of tea in Lahijan city of Guilan Province, Iran (Soheili-Fard *et al.*, 2014). Accordingly, data used in this study were obtained from 30 tea farms from 5 villages in Guilan province of Iran in 2013-2014 crop years.

B. Energy consumption

The amount of inputs used in agricultural production practices (human labor, machinery, diesel fuel, chemical fertilizers, farmyard manure, and biocides) and output (tea yield) were calculated per hectare and then, these data were converted to forms of energy to evaluate the output-input analysis. In order to estimate output and input energy, these input data and amount of output yield were multiplied with the coefficient of energy equivalent. Energy equivalents of inputs and output were converted into energy on area unit. The previous studies (cited in Table 1) were used to determine the energy equivalents' coefficients.

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	(Nabavi-Pelesaraei, 2013b)
2. Machinery	h	62.7	(Nabavi-Pelesaraei, 2013b)
3. Diesel fuel	L	56.31	(Nabavi-Pelesaraei, 2014b)
4. Chemical fertilizers	kg		
(a) Nitrogen		66.14	(Mousavi-Avval, 2011)
(b) Phosphate (P_2O_5)		12.44	(Rafiee et al., 2010)
5. Farmyard manure	kg	0.3	(Khoshnevisan et al., 2013)
6. Biocides	kg	120	(Hamedani et al., 2011)
B. Output			
1. Tea	kg	0.8	(Kitani, 1999)

For instance, diesel fuel energy was estimated from the total fuel used in different farm operations for potato production. Energy consumed was calculated using a conversion factor (1 liter of diesel fuel = 56.31 MJ) and expressed in MJ ha^{-1}. Following the calculation of energy input and output equivalents, to assess the energy efficiency of tea production the indices of energy consumption including energy use efficiency, energy productivity, specific energy (energy intensity) and net energy were calculated as follow (Rafiee *et al.*, 2010):

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

$$\text{Energy productivity} = \frac{\text{Tea yield (kg ha}^{-1})}{\text{Input energy (MJ ha}^{-1})} \quad (2)$$

$$\text{Specific energy} = \frac{\text{Input energy (MJ ha}^{-1})}{\text{Tea yield (kg ha}^{-1})} \quad (3)$$

Net energy = Output energy (MJha^{-1})- Input energy(MJha^{-1}) …(4)

For the purpose of growth and development energy demand in agriculture is divided into direct and indirect energies or renewable and non-renewable energies. Direct energy (DE) covers human labor and diesel fuel, while indirect energy (IDE) includes energy embodied in machinery, chemical fertilizers, farmyard manure and biocides used in the tea farms. Renewable energy (RE) consists of human labor and farmyard manure, whereas non-renewable energy (NRE) includes machinery, diesel fuel, chemical fertilizer and biocides.

C. Artificial neural networks (ANN)

Interest in using artificial neural networks (ANNs) for forecasting has led to a tremendous surge in research activities in the past two decades. They can also be configured in various arrangements to perform a range of tasks including classification, pattern recognition, data mining and process modeling. ANNs are inspired to the human brain functionality and structure, which can be represented as a network of densely interconnected elements called neurons. They consist of a great number of processing elements (neurons) connected to each other and the strengths of the connections are called weights. For the modeling of physical systems, a feed forward back propagation (BP) multilayered perceptron (MLP) structure is commonly used. The main advantages of MLP structures are that, they are easy to use and they require relatively little memory and are generally fast; also they have the ability to learn complex relationships between input and output patterns, which would be difficult to model with conventional algorithmic methods (Pahlavan *et al.*, 2012).

An ANN structure usually consists of a layer of input neurons, a layer of output neurons and one or more hidden layers. In an MLP, there is no connection between the neurons in a given layer, so that the information is transferred from the (l-1)th layer to the lth layer. External datasets enter the network through the input nodes and through non-linear transformations; output values are generated by the output nodes. Hidden nodes with appropriate non-linear transfer functions are used to process the information received by the input nodes (Omid *et al.*, 2009). Based on the above sentences, the energy inputs including human labor, diesel fuel, machinery, nitrogen, phosphate, farmyard manure and were considered as inputs of ANN model; while, tea yield was chosen as only output of ANN model in this study. Several structures were evaluated using the experimental data to determine the best prediction model for the network. 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. (5) (Zhao *et al.*, 2009):

$$O = f\left(T + \sum w_i x_i\right) \quad (5)$$

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

The performance of the network can be evaluated by comparing the error obtained from the converged/combined neural network runs and the measured data.

The error function can be written as (Nabavi-Pelesaraei *et al.*, 2014a):

$$E = \frac{1}{p}\sum_p \sum_k \left(t_{pk} - z_{pk}\right)^2 \quad (6)$$

where 'p' is the index of the p training pairs of vectors, 'k' the index of 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.

The mean square error (MSE) method is the most commonly used indicator of prediction error over all training vectors. MSE is very useful to compare different models; it shows the networks' ability to predict the correct output.

The MSE can be expressed as (Safa and Samarasinghe, 2011):

$$\text{MSE} = \frac{1}{\text{n}}\sum_i^n \left(t_i - z_i\right)^2 \quad (7)$$

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 coefficient of determination (R2) and mean absolute error (MAE) between the predicted and actual values were calculated using the following equations (Pahlavan *et al.*, 2012b):

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2} \right) \quad (12)$$

$$MAE = \frac{1}{n} \sum_{t=1}^{n} \left| (t_i - z_i) \right| \quad (13)$$

where 't_i' and 'z_i' are the predicted and actual output for the i^{th} orchardist, respectively. Basic information on energy inputs of tea production was entered into Excel 2013 spreadsheets and the Matlab (R2014b) software package.

RESULTS AND DISCUSSION

A. Analysis of input-output energy use in tea production

Table 2 shows the quantities of inputs used in whole production life and establishment of tea green leaf and their energy equivalences. Also Fig. 1 shows the distribution percent of the energy associated with the inputs. The results revealed that around 6618 h of human labor and 24 h of machinery power per hectare were required to produce tea in the research area. The total energy input for various processes in the tea production was calculated to be 46144.04 MJ ha^{-1}. The highest average energy consumption of inputs was for nitrogen (23458.72 MJ ha^{-1}) which was accounted for about 51% of the total energy input (Fig. 1), followed by human labor (12971.06 MJ ha^{-1}, 28%). The irregular consumption of nitrogen in alfalfa production is for misunderstandings of farmers in the studied area. Really, we believed the high consumption of chemical fertilizer can be increase the yield per hectare. In other hand, the low price of chemical fertilizers and lack of expert supervision can be effective in the high rate of chemical fertilizer consumption in this region. It should be noted, the average of energy output (from tea yield) was calculated as 8419.47 MJ per hectare with standard deviation of 2356.42 MJ ha^{-1}.

Table 2: Amounts of inputs and output of tea production with their energy equivalent.

Items (unit)	Quantity per unit area (ha)	Total energy equivalent (MJ ha^{-1})	Standard deviation
A. Inputs			
1. Human labor (h)	6617.89	12971.06	3829.08
2. Machinery (h)	24.44	1532.41	667.23
3. Diesel fuel (L)	121.71	6853.63	3406.15
4. Chemical fertilizers (kg)			
(a) Nitrogen	354.68	23458.72	12344.70
(b) Phosphate (P_2O_5)	66.35	825.34	434.32
5. Farmyard manure (kg)	350.90	105.27	86.23
6. Biocides (kg)	3.31	397.61	222.82
The total energy input	-	46144.04	14897.15
B. Output			
1. Tea (kg)	10524.34	8419.47	2356.42

The energy use efficiency, energy productivity, specific energy and net energy of tea production in the Guilan province are listed in Table 3. The energy use efficiency in the production of tea was found to be 0.18. The energy ratio is often used as an index to examine the energy efficiency in crop production. The energy ratio for some crops are reported as 0.02 for basil, 9.03 for eggplant, 4.53 for peanut and 1.29 for watermelon (Pahlavan *et al.*, 2012; Nabavi Pelesaraei *et al.*, 2013a-2013b-2014a). The energy productivity of tea production was calculated as 0.23 kg MJ^{-1}. Obviously, the specific energy was 4.38 in tea production. Moreover, the net energy of tea production was found to be -37724.57 MJ ha^{-1}, which indicates that in this crop production, the energy loss because net energy was negative. As can be seen in Table 3, the energy forms of tea production was including direct, indirect, renewable and non-renewable energies are demonstrated. Accordingly, the average of energy use was computed as 19824.69 MJ ha^{-1}, 26319.35 MJ ha^{-1}, 13076.33 MJ ha^{-1} and 33067.71 MJ ha^{-1} for direct, indirect, renewable and non-renewable energies, respectively.

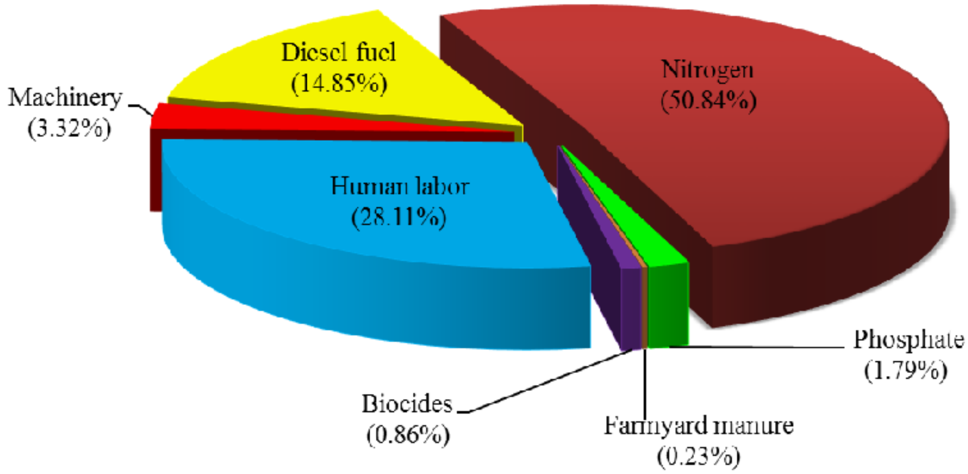

Fig. 1. The share of each input in total energy consumption of tea production.

Table 3: Amount of energy indices and energy form categories of tea production.

Items	Unit	Value
Energy use efficiency	-	0.18
Energy productivity	kg MJ^{-1}	0.23
Specific energy	MJ kg^{-1}	4.38
Net energy gain	MJ ha^{-1}	-37724.57
Direct energy	MJ ha^{-1}	19824.69
Indirect energy	MJ ha^{-1}	26319.35
Renewable energy	MJ ha^{-1}	13076.33
Non-renewable energy	MJ ha^{-1}	33067.71
Total energy input	MJ ha^{-1}	46144.04

The share of energy input as direct, indirect, renewable and nonrenewable forms is illustrated in Fig. 2. With respect to above-mentioned, the total consumed energy input could be classified as direct energy (42.96%), and indirect energy (57.04%) or renewable energy (28.34%) and non-renewable energy (71.66%). This indicates that tea production depends mainly on non-renewable energy (diesel fuel and nitrogen) in the studied area. Therefore, it is clear that non-renewable energy consumption was higher than that of renewable in tea production.

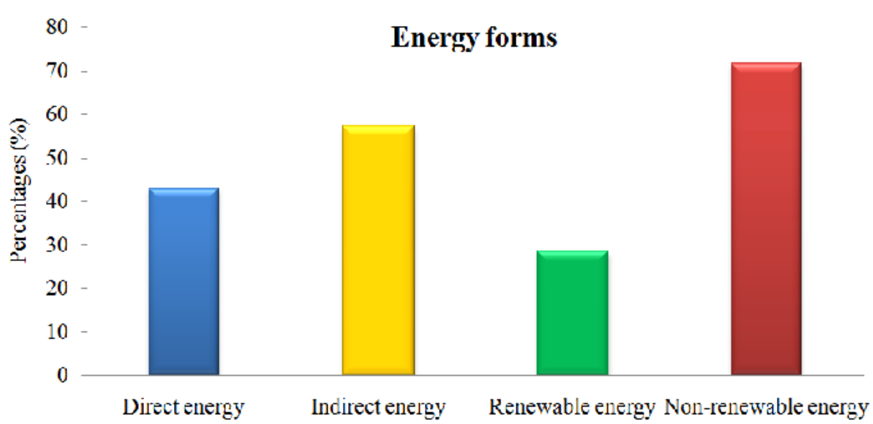

Fig. 2. The contribution of energy forms each input in tea production of Guilan province, Iran.

B. Evaluation and analysis of the ANN model

Several MLP networks were designed, trained and generalized, using the MATLAB R2014b software package. Back propagation algorithm was chosen to build the prediction models.

The best model was consisted of an input layer with seven input variables, two hidden layers with thirteen neurons in each layer, and an output layer with one output variable (7-13-13-1 structure). The results of ANN model are presented in Table 4.

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

Item	R^2	RMSE	MAPE
Tea yield	0.968	0.105	0.006

Based on results, the best topology has the highest coefficient of determination (R2) (with 0.968) and the lowest values RMSE and MAPE. Accordingly, the rate of RMSE and MAPE was computed as 0.105 and 0.006, respectively. So this model was selected as the best solution for estimating the tea production yield on the basis of input energy in surveyed region. Safa and Samarasinghe (2011) reported on a neural network with two hidden layers that can predict energy consumption based on farm conditions (size of crop area), social factors (farmers' education level), and energy inputs (N and P use, and irrigation frequency).

Pahlavan *et al.* (2012) predicted basil production using an ANN model including an input layer (with seven neurons), two hidden layers (with 20 neurons in each layer) and an output layer (with one neuron). In another study, an ANN model with an 11-10-2 structure was developed to model energy consumption in watermelon production (Nabavi-Pelesaraei *et al.,* 2014a).

C. Sensitivity analysis

Sensitivity analysis via ANN ranked and selected the major and input variables through its analysis using partial differential (Nabavi-Pelesaraei *et al.,* 2014a). Sensitivity analysis was performed using the best network selected, in order to assess the predictive ability and validity of the developed models (Table 5). The share of each input item of developed MLP model on desired output (tea yield) can be seen clearly. Sensitivity analysis was used to test the robustness of the results of a model or system in the presence of uncertainty and increased the understanding of the relationships between input and output variables in a system or model (Nabavi-Pelesaraei *et al.,* 2014a). The results indicated that the farmyard manure had the highest value of sensitivity analysis with 0.058 on tea yield; followed by diesel fuel (0.050) and biocides (0.042). In another hand, the lowest rate of sensitivity was belonged to nitrogen with 0.019 in tea production of Guilan province, Iran.

Table 5. Sensitivity analysis results for input energies.

Inputs	**Sensitivity value on tea yield**
1. Human labor	0.033
2. Machinery	0.021
3. Diesel fuel	0.050
4. Nitrogen	0.019
5. Phosphate (P_2O_5)	0.021
6. Farmyard manure	0.058
7. Biocides	0.042

CONCLUSION

Total energy consumption and yield of tea production were 46144.04 MJ ha^{-1} and 8419.47 kg ha^{-1}, respectively. Nitrogen had the highest share of energy use among all inputs, at 50.84%; followed by human labor with 28.11%. The average rates of energy indices, including energy use efficiency, energy productivity, specific energy and net energy were calculated at 0.18, 0.23 kg MJ^{-1}, 4.38 MJ kg^{-1} and -37724.57 MJ ha^{-1}, respectively. The results of energy forms analysis indicated that the share of indirect and non-renewable energy was more than direct and renewable energies, significantly. The best model for predicting of tea yield was an ANN model with a 7-13-13-1 structure. With respect to the best topology, R2, RMSE and MAPE was found to be as 0.968, 0.105 and 0.006, respectively. The results of the sensitivity analysis showed that farmyard manure with 0.058 had the highest rate of sensitivity; followed by diesel fuel with 0.050.

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