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A neural network based modeling of energy inputs for predicting economic indices in seed and grain corn production

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ABSTRACT

In this study, various Artificial Neural Networks (ANNs) were developed to determine the economics indices for seed and grain corn production in Ardabil province, Iran. For this purpose, the data was collected by a face-to-face interview method from 144 corn farms during 2011 and analyzed. The results indicated that total energy input for seed and grain corn productions was about 45162.77 and 35198.11, respectively. The developed ANN was a multilayer perceptron (MLP) with six neurons in the input layer (human labor, machinery, diesel fuel, chemical fertilizer, chemicals, seed), one, two and three hidden layer(s) of various numbers of neurons and four neuron (BCR, P, TR, NR) in the output layer. The results of ANNs analyze showed that the best MLP network models for predicting economic indices in seed and grain corn production had (6-6-10-4) and (6-4-8-4) topologies, respectively. For these topologies, MSE, MAE and R^2 calculated. The ANN approach appears to be a suitable method for modeling output energy, fuel consumption, CO_2 emission, yield, and energy consumption.

Introduction

Corn is a plant that is cultivated in order to produce grain, seed and silage for feeding livestock. Ardabil is one of the most important centers for seed and grain corn production in Iran. All sorghum and nearly 90% of seed corns are produced in this region. High energy use efficiency in agriculture will help to minimize the environmental problems, prevent destruction of natural resources, and promote sustainable agriculture as an economical production system. The development of energy efficient agricultural systems with low input energy compared to the output of food can reduces the greenhouse gas emissions from agricultural production systems (Dalgaard et al., 2001).

Energy consumption in agriculture is one of the important and effective factors in sustainable agricultural production, because it reduces costs and saves, preserved the fossil resources and reduce the amount of air pollution and greenhouse gas emissions (Uhlin, 1998). Nowadays, agricultural sector has become more energy-intensive in order to supply more food to increasing population and provide sufficient and adequate nutrition. However, considering limited natural resources and the impact of using different energy sources on environment and human health, it is substantial to investigate energy use patterns in agriculture (Shamabadi and Faeznia, 2013). Kaul et al. (2005) examined corn and soybean yield by artificial neural networks (ANNs) and logistic regression in states, regions and local levels in Maryland. ANN training parameters such as the number of hidden layer nodes had important influence on performance prediction. The results showed that ANN models are more accurate than regression methods. The coefficient of determination (R^2) and RMSE for ANN were 0.77, 1036, whereas for the linear regression were 0.42 and 1356, respectively. Zanganeh et al. (2011) compared results of two different methods (parametric and ANN models) for evaluating economical indices of potato production such as economical productivity, total costs of production and benefit to cost ratio.

Tripathy and kumar (2009) using neural networks to Predict the temperature of food during drying (sun dryer) that intensity of solar radiation and air temperature were considered as network parameters. Different data 9 days of each month was considered for training and testing the network. The result show that neural network with four neurons in the hidden layer and sigmoid function and error back propagation algorithm was the best neural network to predict the temperature. Momenzadeh et al (2011) studied the effect of different temperatures (30, 40, 50, 60 Ċ) and dryer power(180, 360, 540, 720, 900 W) in the time it takes to drying (low humidity) for corn using neural networks. The results showed that increasing the drying temperature due to decreases the time required to reduce the moisture content to 5% level. Power dryer, different temperatures and moisture content of corn were considered as the network inputs and time required for drying corn as the network output that best Network Model was achieved with Hyperbolic tangent transfer function and error back propagation algorithm.

Based on the literature, there has been no study on modeling seed and grain corn production with respect to input energies using ANNs. Thus, the aim of this paper has been to reach the following goals: Firstly, determine energy consumption in seed and grain corn production, and secondly, to adapt ANNs as a tool for predicting the economic indices in seed and grain corn production as a function of inputs energy consumption in the study area.

Material and methods

Case study and data collection

Ardabil is one of the most important agricultural centers in Iran. The province is located in northwest of Iran, within 34^{o} 04′ and 39^{o} 42′ north latitude and 47^{o} 55′ and 48^{o} 55′ east longitude.

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Pars Abad city, located at the northern part of the province, produces about 90% of seed corns and 100% sorghum in this region. The necessary data to conduct this research were collected through face to face questioners including the hour of machinery usage and labors, diesel fuel, seeds, fertilizers and chemicals consumption per hectare and the yield of seed and grain corns. The total number of filled questionnaires for each product was 72. The amount of inputs (chemicals, human labor, machinery, seeds, fertilizers and diesel fuel) were calculated per hectare and then these data were converted to forms of energy to evaluate the outputs (economics indices).

The amount of inputs (chemicals, human labor, machinery, seeds, fertilizers and diesel fuel) and outputs (seed and grain corn yields) were calculated per hectare and then these data were converted to forms of energy to evaluate the input energies and output indices. In order to estimate and input energy, these input data were multiplied with their coefficient of energy equivalents. Energy equivalents of inputs were converted in to energy on area unit. For estimating the sample size, Cochrane formula and Morgan's table were used (Banaeian and Zangeneh, 2011):

$$n = \frac{Nt^2 s^2}{Nd^2 + t^2 s^2} \qquad (1)$$

where n is the required sample size; N is the size of the statistical society (The number of corn farmers); t is the reliability coefficient (1.96 which represents the 95% reliability); s is the standard deviation; d is the acceptable error (the permissible error in the sample size was defined for 95% confidence). Based on this formula, number of sampling of 76 farms was obtained. For more accuracy 144 farmers were considered. Machines, human labor, diesel fuel, fertilizers, seeds and chemicals as input and the output value was taken as the generating and the amount of each input for the calculation of energy consumption per hectare. Energy input and energy output are presented in Table 1.

Fig. 1 shows the average percentage share of energy consumption in the production of the two products by inputs. In recent years, many researchers have been investigated the energy use for agricultural crop production. During the past 15 years there has been a substantial increase in the interest on Artificial neural networks. The basis of ANN modeling methods is biological neuron activities. Neurons in the brain learn to respond to a situation from a collection of examples represented by inputs and outputs.

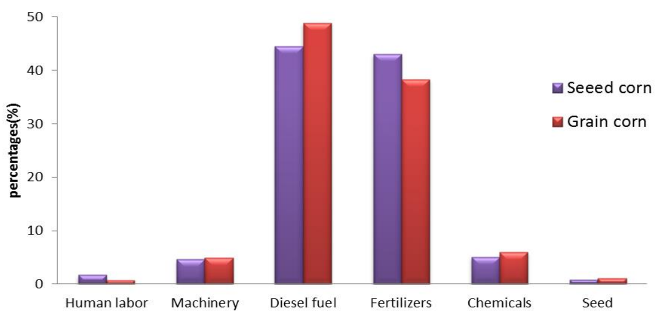

Figure 1. The share of total mean energy input in corn production

Artificial neural network modeling

In an ANN, neurons are grouped in layers. In complex problems more than one layer is necessary; these neural networks are called multilayer neural networks whose most prominent representative is the Multi- Layered Perception (MLP). Signals are sent from input layers through hidden layers to the output layer. In some networks, the output of neurons is feed back to the same or previous layers. In most studies, a feed-forward Multi-Layered Perception (MLP) paradigm trained by a gradient descent learning method is used. Due to its documented ability to model any function, a MLP has been selected to develop apparatus, processes, and product prediction models more than other feed-forward networks (Kalogirou, 2001). The transfer functions may be a linear or a non-linear function. The output depends on the particular transfer function used. This output is then sent to the neurons in the next layer through weighted connections and these neurons complete their outputs by processing the sum of weighted inputs through their transfer functions.

Advantage of ANNs is that outcomes may be predicted using all available environmental information as concurrent inputs. Moreover, in terms of commercial deployment, ANNs often result in very accurate predictions without any real need to understand the underlying mechanisms and relationships (Ehret et al., 2011).

In order to estimate economic indices in the region, we introduced various input energies used for seed and grain corn production including machinery, human labor, diesel fuel, fertilizers, chemicals and seeds energies as the input variables; also the seed and grain corn economic indices defined as the desired output parameters in the model. Different structures with one to three hidden layers have been trained and evaluated aiming at finding the one that could result in the best overall performance in estimation economic indices based on energy consumptions in both products. For the hidden layers the hyperbolic tangent transfer functions was used, and for the output layer a sigmoid tangent transfer function was applied as desired for estimating problems. In this study, data were divided into three parts; 65% of data are used for training, 15% for cross validation and 20% were allocated for network testing.

In this study, calculations were carried out using the Excel software programs. All the data collected of seed and grain corn fields were imported into Excel 2010 worksheets and the energy values were calculated and analyzed. ANN models were developed in Neuro Solutions 5.07 package for estimating indices. In order to measure the strength of a linear relationship between variables the coefficient of determination (R^2) was estimated for models and analyzed(Omid et al., 2009).

To objectively evaluate the best network created, different statistical indices were used. These indices were mean squared error (MSE), mean absolute error (MAE) and coefficient of determination (R^2):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{estimated} - Y_{target}\right)^2 \qquad (2)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}\left(Y_{estimated} - Y_{target}\right)^2}{\sum_{i=1}^{n}\left(Y_{target}\right)^2}\right) \qquad (3)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_{estimated} - Y_{target}}{Y_{target}}\right| \times 100 \qquad (4)$$

where Y_{target} and $Y_{estimated}$ are actual and predicted current values of seed and grain corn yield by the models, and n is the number of exemplars in data set.

Result and discussion

Economic indicators estimation

Table 2 shows the economic indices in seed and grain corn production.

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

Input	Unit	Energy equivalent (MJ unit)	Refs.
A. Input			
1.Human labor	H	1.96	(Kitani, 1999)
2. Machinery	Kg	62.7	(Banaeian and Zangeneh, 2011)
3.Diesel fuel	L	47.8	(Kitani, 1999)
4.Fertilizers			
Nitrogen(N)	Kg	66.14	(Erdal et al., 2007)
Phosphate(P_2O_5)	Kg	12.44	(Erdal et al., 2007)
Liquid	L	85	(Esengun, 2007)
5. Chemicals			
Atrazine	Kg	190	(Kitani, 1999)
24D	L	85	(Kitani, 1999)
Other	L	101.2	(Banaeian and Zangeneh, 2011)
6.Seed (corn)	Kg	14.7	(Houshyar et al., 2012)
B. Output			
Corn	kg	14.7	(Houshyar et al., 2012)

Table 2. Economic indices in corn productions

Indices	Seed corn	Grain corn
TR: Total Return ($ ha^{-1})	4894.88	1252.29
TC: Total Cost ($ ha^{-1})	1520.84	1015.56
NR: Net Return ($ ha^{-1})	3374.04	236.73
P: Productivity (Kg $$^{-1}$)	0.0609	0.1807
BCR: Benefit cost Ratio	3.21	1.28

Table 3. Estimation economic indices for seed corn using Artificial neural network

Indices	R2	MSE	MAE
TR: Total Return ($ ha^{-1})	0.9974	799419.7	15.386
BCR: Benefit cost Ratio	0.9950	0.0055538	0.040480338
Productivity (Kg $$^{-1}$)	0.9990	0.000216	4.025
NR: Net Return ($ ha^{-1})	0.9974	2629473	30.471

Table 4. Estimation economic indices for grain corn using Artificial neural network

Indices	R2	MSE	MAE
TR: Total Return ($ ha^{-1})	0.7934	4490069	14.688
BCR: Benefit cost Ratio	0.7987	0.008096	0.0272214
Productivity (Kg $$^{-1}$)	0.8909	0.2322	6.5593
NR: Net Return ($ ha^{-1})	0.8954	2708469	13.845

The benefit cost ratio is more in seed corn rather to grain corn that due to is the high price of seed corn rather to grain corn. productivity is the amount of a product obtained per unit of total cost.

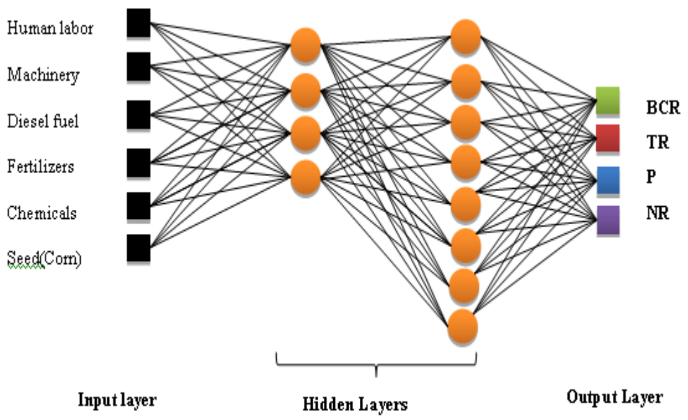

Figure 2. The best Topology of a fully connected four-layered MLP network for estimation grain corn economic indices

Artificial neural network and economic indices

The best model for predicting indices were FFNNs with two hidden layers and trained with LM algorithms, with hyperbolic tangent transfer functions for hidden layers and Sigmoid tangent transfer function for output layer. Tables 3 and 4 show performance of various FFNN models that have been developed to predict seed and grain corn economic indices by using different number of neurons in each of hidden layers. The error estimation indices of the represented FFNN for seed and grain corn indices were calculated according to Eqns. (2) to (4).

Among these, the best model for determine economic indices for seed corn was consisted of an input layer with six input variables, two hidden layers with six and ten neurons in each layer and an output layer with four output variable (i.e., a 6-6-10-4 structure). This topology had the highest coefficient of determination and the lowest values of MAE, MSE. So this model was selected as the best solution for estimating the seed corn economic indices on the basis of input energy in surveyed region.

The best model for estimation indices in grain corn was consisted of an input layer with six input variables, two hidden layers with four and eight neurons in each layer(see Fig. 2),, and an output layer with four output variable (i.e., a 6-4-8-4 structure). This topology had the highest coefficient of determination and the lowest values of MAE, MSE. So this model was selected as the best solution for estimating the grain corn production yield on the basis of input energy in surveyed region.

Khajeh et al. (2012) used neural network with multi-layer perceptron to prediction the amount of oil extracted from Diplotaenia cachrydifolia. Network inputs was four parameter include temperature, Pressure, time, volume and output the network amount recoverable oil. For training network was used Levenberg Marquat algorithm. The results showed that the neural network with five neurons in the hidden layer have the most accurate in predicting the oil extracted. Prediction output value associated with the actual output had coefficient of determination (R^2) of 0.9998 and 0.9978 for seed and grain corns, respectively.

Conclusion

Seed and grain corn production consumed a total energy of 45162.77 and 35198.11 respectively. The energy input of chemical fertilizer and diesel fuel have biggest share of the total energy inputs. The main objective of this study was to determine energy consumption, model and predict economic indices for seed and grain corn production on the basis of input energies. Accordingly, several ANN models were developed and evaluated. The prediction accuracy of the models was evaluated using different statistical indices. Among the studied structures, two ANN models, namely, one with 6-6-10-4 topology and one with 6-4-8-4 topology, were the best models for predicting seed and grain corn economic indices, respectively. Model output value associated with R^2, MSE and MAE values for seed and grain corn.

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