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A Neural Network Based Modeling and Sensitivity Analysis of Energy Inputs for Predicting Seed and Grain Corn Yields

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ABSTRACT

In this study, several artificial neural networks (ANNs) were developed to estimate seed and grain corn yields in Parsabad Moghan, Iran. The data was collected by a face-to-face interview method from 144 corn farms during 2011. The energy ratios for seed and grain corns were calculated as 0.89 and 2.65, respectively. Several multilayer perceptron ANNs with six neurons in the input layer and one to three hidden layers with different number of neurons in each layer and one neuron (seed or grain corn yield) in the output layer was developed and tested. Energy inputs including fertilizers, biocides, seeds, human labor, diesel fuel and machinery were considered as explanatory variables for the input layer. The best model for predicting seed and grain corn yields had 6-4-8-1 and 6-3-9-1 topologies, respectively. Model output value associated with the actual output had coefficient of determination (R^2) values of 0.9998 and 0.9978 for seed and grain corn, respectively. The corresponding regression models had R^2 values of 0.987 and 0.982, respectively. Sensitivity analysis showed that in seed corn production, diesel fuel and machinery, and in grain corn, diesel fuel and seeds consumption have the greatest effect on production yield.

Keywords: Artificial neural networks, Corn production, Energy input, Regression, Sensitivity analysis.

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INTRODUCTION

In terms of production in the world, Corn (*Zea mays* L.) is considered as the third most important cereal, after wheat and rice (Ashofteh Beiragi *et al.*, 2011). Corn is a plant that is cultivated in order to produce grain, seed, and silage for feeding livestock. Agricultural sustainability is facing substantial challenges from global changes: while there are heightened requirements to maintain or increase food production, agriculture is being confronted with climate change, continuing degradation of its natural resource base, and increasing energy costs (Thorburn *et al.*, 2011).

Energy requirements in agriculture are divided into groups of direct, indirect, renewable, or non-renewable. Direct energy to do work (operation) varies as land preparation, irrigation, threshing, harvesting, and transport of agricultural inputs. Therefore, direct energy is used directly on farms. A wide variety of energy forms, which can be directly used, include diesel fuel and electricity to pump water for irrigation. Indirect energy is the energy contained in the packaging, transportation, chemical fertilizers, herbicides, and agricultural machines in use (Ozkan *et al.*, 2007). High energy use efficiency in agriculture will help to minimize the

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environmental problems, prevent destruction of natural resources, and promote sustainable agriculture as an economical production system.

In the last few decades, artificial neural networks (ANNs) 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. ANN is one of the intelligent techniques which is flexible and doesn't call for much physically complex processes (Yazdani *et al*., 2009). ANN is an optimization algorithm in which it is attempted to mathematically model the learning process. The model is a simple approximation of such a complex process, but it utilizes the basic foundations and concepts inherent in the learning processes of humans and animals. ANNs are universal function approximators that typically work much better than the more traditional (polynomial) function approximation methods. The first ANN model was first presented by McCulloch and Pitts (1943) and later extended by others. Indeed, ANNs have attracted a lot of interest in the past decade and in certain processes. Kaul *et al.* (2005) examined corn and soybean yield by ANNs and logistic regression based on location and soil type ANN training parameters, such as the number of hidden layer nodes, had an important influence on performance prediction. The results showed that ANN models were more accurate than regression analysis in forecasting corn and soybean yield. Jiu-Quan *et al.* (2009) applied statistical models and artificial neural network to predict soybean growth during the 4-year period (1998-2001) in Mississippi under irrigated conditions. The effective potential factors for modeling in soybean growth and development, which includes weeds, pests, diseases, and drought, were handled. Models of soybean growth and development were divided into two groups: vegetative growth (10 steps) and generative growth (8 steps). It was shown that planting date, maturity period (late growth period), and time distance of sowing date, were the most important factors in development of models to predict soybean growth and development. Azadeh *et al.* (2008) used multi-layer perceptron (MLP) for forecasting the monthly electrical energy consumption of Iran. Computer simulation was developed to generate random variables for monthly electricity consumption. This was achieved to foresee the effects of probabilistic distribution on monthly electricity consumption. When function approximation is the goal, the MLFN model will often deliver close to the best fit. Omid *et al.* (2009) simulated drying kinetics of pistachio nuts using a MLFN. A comparative study among MLFN and empirical models was also carried out by the authors. They showed that MLFN model was more accurate than the empirical models. Zangeneh *et al.* (2011) compared results of the application of two different approaches, namely, parametric model (PM) and ANN models, for assessing economical indices including economical productivity, total costs of production, and benefit to cost ratio of potato crop. They used Cobb-Douglas production function for PM and MLFN for implementing ANN models. Pahlavan *et al.* (2012**a**) predicted greenhouse basil production using ANNs.

Due to the importance of prediction models for corn yield, the aim of this study was: (a) to investigate if ANNs can be used as a tool for predicting the products yield by using inputs energy consumption, and (b) to compare regression results with a proposed ANN prediction model.

MATERIALS AND METHODS

Ardebil province of Iran is one of the most important agricultural centers in the country. The province is located in northwest of Iran, within 34° 04′ and 39° 42′ north latitude and 47° 55′ and 48° 55′ east longitude. Parsabad city is located in the northern part of the province and is the most important center for seed and grain corn

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production in the country. Approximately 90% of Iranian seed corns and 100% sorghum is produced in this region. The area devoted to grain and seed corns cultivation in 2011 were 15,832.5 and 963.5 ha, respectively. The necessary data to conduct this research were collected through face to face questioners including the hours 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) 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-output energies. In order to estimate output and input energies, these input data and output yields were multiplied by their coefficient of energy equivalents.

Energy equivalents of inputs and outputs were converted into energy per unit area. To estimate the sample size, Cochrane formula and Morgan's table were used (Kitani, 1999). Energy input and output are presented in Table 1. Machines, human labor, diesel fuel, fertilizers, seeds and chemicals as input, and the output value was taken as seed or grain corn yield. Figure 1 shows the average percentage share of energy consumption in the production of the two products by different inputs.

All calculations were carried out using the SPSS 20 and Excel software programs. All the data collected from the seed and grain corn fields were imported into Excel 2010 worksheets and the energy values were calculated and analyzed. In order to measure the strength of a linear relationship between the variables, the coefficient of determination (R^2) was estimated for the models and analyzed.

Artificial Neural Networks Modeling

ANN is a form of artificial intelligence that imitates some functions of the human brain. ANN is a relatively new nonlinear statistical technique. It can solve the problems that do fit the conventional statistical methods. ANN consists of simple synchronous processing elements, called neurons, which are inspired by biological nerve system. The network comprises of a large number of simple processing elements that are connected to each other by the weighted connections, according to the required specified architecture. These networks learn from the training data by adjusting the connection weights (Khashei-Siuki *et al*., 2011). ANN is a modeling method to simulate complex systems,

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	(Pahlavan *et al*., 2012b)
2. Machinery	kg	62.7	(Zangeneh *et al*., 2010a)
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	(Pahlavan *et al*., 2012c)
Liquid	L	85	(Esengun *et al*., 2007)
5. Chemicals			
Atrazine	kg	190	(Kitani, 1999)
24D	L	85	(Kitani, 1999)
Others	L	101.2	(Zangeneh *et al.,* 2010a)
6.Seed (corn)	kg	14.7	(Houshyar *et al*., 2012)
B. Output			
Corn	kg	14.7	(Houshyar *et al*., 2012)

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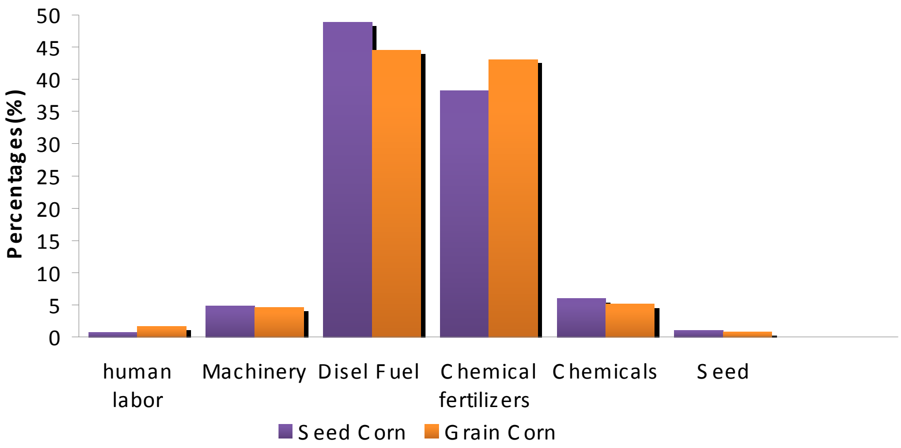

Figure 1. The share of each input in the mean total energy consumption in corn production.

especially nonlinear systems, based on learning a set of training data. The obtained knowledge is not stored as equations, but is distributed throughout the network in the form of connection weights between neurons (Omid *et al.*, 2009). The structure of ANN is an important factor that influences the learning performances of networks. The multilayer perceptron (MLP), known as the feed-forward neural network (FFNN), have the capability of arbitrary input-output mapping, therefore, they are strong in forecasting. MLP, as the most successful and the most common ANN model from a number of ANNs models, is used in the present study. The neurons carry out the same operation; the sum of their weighed inputs. Then, they apply the result to a non-linear function such as hyperbolic tangent (TANH) named activation function to produce output for a unit. A typical feed forward ANN is shown in Figure 2.

The input from each neuron in the input layer is multiplied by an adjustable connection weight. At each neuron, the weighted input signals are summed and this combined input then passed through a non-linear transfer function (f) to produce the output of the neuron. The output of one neuron is the input of the neurons in the next layer. The process in the MLFN model that consists of a single hidden layer can be summarized as (Omid *et al.*, 2009):

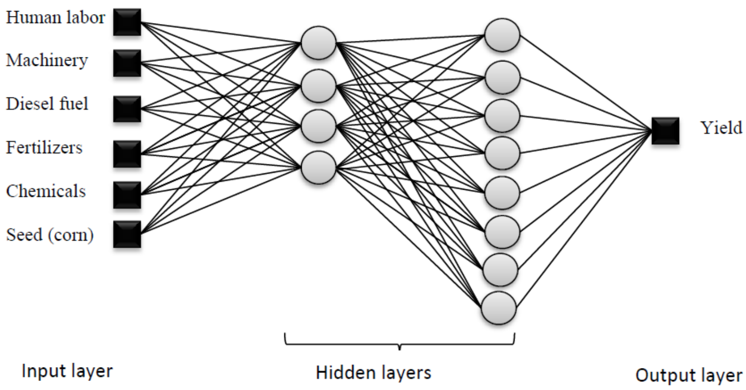

Figure 2. The best Topology of a fully connected four-layered MLP network for estimation of seed corn yield.

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$$y_k = f_2(w_{k0} + \sum_{j=1}^{H} w_{kj} f_1(w_{j0} + \sum_{i=1}^{I} w_{ji} x_i)) \quad (1)$$

Where, x_i is the input value to node i of the input layer, H_j is the hidden value to node j of the hidden layer, and y_k is the output at node k of the output layer (O). An input layer bias term $I_0 = 1$ with bias weights w_{j0} and an output layer bias term $H_0 = 1$ with bias weights w_{k0} are included to permit adjustments of the mean level at each stage. For the purpose of function approximation, the transfer functions in Equation (1) are of the following types:

$$f_1(x) = \tanh(x) \quad (2)$$

$$f_2(x) = x \quad (3)$$

In the MLFNs, error minimization can be obtained by a number of procedures including gradient descent (GD), Levenberg-Marquardt (LM), and conjugate gradient (CG). MLFN are normally trained with an error back-propagation (BP) algorithm. The knowledge obtained during the training phase is not stored as equations or in a knowledge base but is distributed throughout the network in the form of connection weights between neurons. It is a general method for iteratively solving for weights and biases. BP uses a GD technique that is very stable when a small learning rate is used, but has slow convergence properties. Several methods for speeding up BP have been used, including adding a momentum term or using a variable learning rate. In this paper, GD with a momentum (GDM) algorithm is used that is an improvement to the straight GD rule in the sense that a momentum term is used to avoid local minima, speed up learning, and stabilize convergence (Omid *et al.,* 2009).

To model corn yield in the region, a variety of energies such as diesel fuel, labor, biocides, machinery, fertilizer and seed are used as input variables to ANNs and seed and grain corn yields as output parameter of the models. In this study, 65% of the data are used for training, 15% for cross validation, and 20% were allocated for network testing.

In order to estimate corn production in the region, we introduced various input energies used for seed and grain corn production including machinery, human labor, diesel fuel, fertilizers, other chemicals, and seeds energies as the input variables; also, the corn yield was defined as the desired output parameter in the model. Several MLP network architectures with one, two, and three hidden layers were trained and evaluated aiming at finding the one that could result in the best overall performance. In this work, the learning rule of GDM was considered. No transfer function for the first layer was used. For the hidden layers, the hyperbolic tangent transfer functions was used, and for the output layer, a linear transfer function was applied as desired for estimating problems. A program was developed in NeuroSolutions 5.07 package for the feed forward and back propagation network (Omid *et al*., 2009).

Performance Analysis

To objectively evaluate the performance of the networks, four different statistical indicators were used, namely, mean squared error (MSE), mean absolute error (MAE), coefficient of determination (R^2), and mean absolute percentage error (MAPE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{estimated} - Y_{target}\right)^2 \quad (4)$$

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

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_{estimated} - Y_{target}}{Y_{target}}\right| \times 100 \quad (6)$$

Where, Y_{target} and $Y_{estimated}$ are actual and predicted current values of corn yield by the models, respectively. Amongst the above statistical measures, *MAPE* is the most important statistical property in that it makes

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use of all observations and has the smallest variability from sample to sample. *MAPE* is understandable to a wide range of users, therefore, it is often used for reporting.

RESULTS AND DISCUSSION

Regression Analysis

The results showed that, in the production of seed and grain corns, diesel fuel and fertilizers had the biggest shares and the seeds and human labor had the lowest share in energy consumption. Figure 1 shows the average percentage share of energy consumption in the production of the two products by inputs. The average yield of seed corn was 2,753.33 kg ha^{-1} and that of grain corn was 6,362.5 kg ha^{-1}. The energy ratio for seed and grain corns was calculated as 0.89 and 2.65, respectively. Net energy for seed corn was less than zero, whereas it was positive for grain corn. Therefore, it can be concluded that, in seed corn production, energy is being lost. The portion of direct and indirect input energies in total energy input were 46 and 54% for seed, and 50 and 50%, for grain corns, respectively. Mohammadi and Omid (2010) found negative values for the net energy of greenhouse vegetables production in Iran. In addition, because of high consumption of diesel and electricity and high chemical fertilizers energy due to lack of soil analysis in the studied area, energy use efficiency, energy productivity, and net energy were low.

Multiple linear regression (MLR) analysis was conducted in order to compare the determined regression coefficients with ANN results. MLR coefficients are represented in Equations' [7] and [8]:

Seed corn MLR model:

$$Yield_{Seed} = -0.651Labor - 0.203Fuel + 0.051Fertilizer + 0.218Chemicals + 2.714Machinery \quad (7)$$

Grain corn MLR model:

$$Yield_{Grain} = -0.185Labor - 0.483Fuel + 0.015Fertilizer + 0.667Chemicals + 7.547Machinery \quad (8)$$

The values of R^2 of the MLR model for seed and corn yields were 0.987 and 0.982, respectively.

The results of regression analysis indicated that machinery energy input had major impact (2.714) on seed corn yield while the coefficient values of human labor and diesel fuel were -0.651 and -0.203, respectively.

Artificial Neural Network and Prediction of Products Yield

The best models for predicting seed corn yield were networks with two hidden layers and trained with Levenberg-Marquardt algorithms, with hyperbolic tangent transfer functions for hidden layers and linear transfer function for output layer. Tables 2 and 3 show performance of various ANN models that have been developed to predict, respectively, seed and grain corn yield by using different number of neurons in each of the hidden layers. The error estimation indices of the represented ANN and MLR models for seed and grain corn prediction were calculated according to Equations' (4) to (6). The results are represented in Table 4.

Among these, the best model for seed corn prediction consisted of an input layer with six input variables (chemicals, human labor, machinery, seeds, fertilizers, and diesel fuel), two hidden layers with four and eight neurons in each layer (see Figure 2), and an output layer with one output variable i.e. 6-4-8-1 structure, as bolded in Table 2. This topology has the highest coefficient of determination (0.9998) (Table 2 and Figure 3) and the lowest

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Table 2. Examples of models developed to estimate seed corn yield with different number of neurons in the hidden layers (HL).

Model*	HL_1	HL_2	HL_3	R^2	*MSE*	*MAE*	*MAPE* (%)
1	8	10	0	0.9992	0.000062	0.000060	2.298
2	6	6	0	0.9210	0.008178	0.071002	2.882
3	7	10	0	0.9763	0.003533	0.000044	5.433
4	6	8	0	0.8877	0.015424	0.066650	2.675
5	7	10	0	0.9306	0.007362	0.072970	6.169
6	7	10	10	0.9187	0.008422	0.075039	2.994
7[a]	**4**	**8**	**0**	**0.9998**	**0.000009**	**0.001704**	**0. 071**
8	5	8	0	0.8901	0.010462	0.086446	0.339
9	3	7	0	0.9916	0.000077	0.006345	0. 248
10	2	6	9	0.9890	0.001265	0.020789	0. 884
11	4	12	0	0.9116	0.018461	0.106544	4.117
12	15	18	0	0.9237	0.006984	0.053381	2.127
13	4	0	0	0.9934	0.000601	0.016155	0.801
14	2	4	0	0.5508	0.051133	0.164226	6.363
15	2	4	0	0.9964	0.000350	0.014511	0. 655
16	5	13	0	0.9131	0.008869	0.059572	2.439
17	4	11	15	0.9156	0.009447	0.073755	6.511
18	9	5	0	0.7459	0.032053	0.133612	6.289
19	6	10	0	0.9990	0.000101	0.003899	0. 199
20	7	9	0	0.9625	0.005731	0.044390	2.942

[a] Optimum network for seed corn with 6-4-8-1 structure is bolded.

Table 3. Examples of models developed to estimate grain corn yield with different number of neurons in the hidden layers.

Model [a]	HL_1	HL_2	HL_3	R^2	*MSE*	*MAE*	*MAPE* (%)
1	4	6	0	0.5311	0.190184	0.296370	4.494
2	10	15	0	0.1616	0.384286	0.380808	5.851
3	6	8	12	0.4402	0.217025	0.355461	5.583
4	6	11	0	0.8155	0.111085	0.194731	2.847
5	6	11	14	0.7468	0.138050	0.259163	4.005
6	8	12	0	0.6424	0.154033	0.241071	3.880
7	8	0	0	0.4890	0.220527	0.369822	5.731
8	4	8	12	0.5168	0.188386	0.259906	4.658
9	10	10	0	0.5384	0.190683	0.285573	4.451
10	5	10	0	0.5631	0.180759	0.326158	5.013
11	4	7	10	0.6686	0.158899	0.257312	3.840
12	2	7	0	0.7236	0.130845	0.238814	3.604
13	5	8	0	0.5462	0.199026	0.262698	4.045
14	6	10	0	0.4872	0.224805	0.272071	3.929
15	6	11	0	0.1613	0.350998	0.357193	5.465
16	3	8	11	0.7184	0.135170	0.226228	3.357
17	12	0	0	0.2431	0.309238	0.359715	5.518
18	4	9	14	0.5032	0.214045	0.290817	4.583
19[a]	**3**	**9**	**0**	**0.9978**	**0.000759**	**0.007601**	**0. 106**
20	3	9	0	0.9974	0.829142	0.010766	0. 152

[a] Optimum network for grain corn with 6-3-9-1 structure is bolded.

Table 4. Statistical analysis of the best ANN models and MLR estimation.

Output	Method	R^2	*MSE*	*MAE*	*MAPE* (%)
Seed corn	ANN	0.9998	0.000009	0.0017	0. 07
	MLR	0.9888	0.821862	0.2509	9.38
Grain corn	ANN	0.9978	0.000759	0.0075	0. 10
	MLR	0.9812	0.812057	0.7367	11.11

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Table 5. Comparison between actual and estimated yield using the study data.

Seed corn			Grain corn		
Actual yield	ANN estimation	MLR estimation	Actual yield	ANN estimation	MLR estimation
2200	2190.35	2311.91	6500	6500.02	6932.44
2450	2450.06	2799.95	5800	5800.00	6559.39
2600	2600.80	2572.08	6700	6699.99	6630.47
2700	2700.41	3233.72	6300	6299.93	6986.10
3100	3100.74	3413.96	6000	5999.89	5862.70
3200	3201.01	2772.24	6300	6299.95	6986.10
2800	2801.48	2572.39	7200	7199.91	5651.52
2800	2800.27	2572.39	5300	5299.81	6448.24
2300	2302.68	2692.49	7200	7305.55	5651.52
2750	2750.72	2651.88	6800	6800.02	6679.43
2800	2800.27	3015.50	7100	7099.89	6328.79
2600	2600.34	2358.05	7200	7200.13	5651.52
2300	2295.02	2031.66	6600	6600.04	7316.93
3100	3100.40	3035.45	6700	6700.01	6630.47

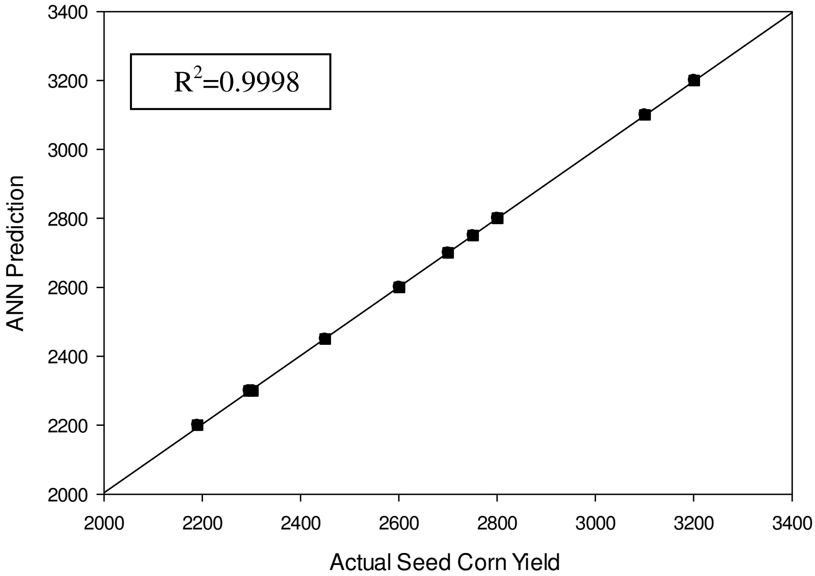

Figure 3. Regression graphs of ANN and actual output value of seed corn.

values of *MAE* (0.001704), *MSE* (0.000009) and *MAPE* (0. 071), indicating that the ANN predicted seed corn yield by this model tends to follow the corresponding actual ones quite closely as shown in Table 5. Therefore, this model was selected as the best solution for estimating the seed corn production yield on the basis of input energy in the surveyed region.

The best model for grain corn prediction consisted of an input layer with six input variables (chemicals, human labor, machinery, seeds, fertilizers and diesel fuel), two hidden layers with three and nine neurons in each layer, and an output layer with one output variable i.e. 6-3-9-1 structure, highlighted in Table 3. This topology has the highest coefficient of determination (0.9978) and the lowest values of *MAE* (0.007601), *MSE* (0.000759) and *MAPE* (0. 106), indicating that the ANN predicted grain corn yield by this model

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tends to follow the corresponding actual ones quite closely. Therefore, this model was selected as the best solution for estimating the grain corn production yield on the basis of input energy in the surveyed region.

Mohammadi *et al.* (2010) devised ANN models to estimate yield level of kiwifruit production in Mazandaran province of Iran. They used annual energy consumption per hectare of fruit production by different inputs as input variables and the yield level of fruit as output parameter. From this study, they concluded that the ANN model with 6-4-1 structure was the best model for predicting the kiwifruit yield in the surveyed region. Rahman and Bala (2010) reported that a model with 6-9-5-1 structure i.e., a network having an input layer with six neurons, two hidden layers with 9 and 5 neurons and one neuron in the output layer, was the best model for predicting jute production in Bangladesh. Pahlavan *et al.* (2012a) developed various ANN models to estimate the production yield of greenhouse basil in Iran. The proposed ANN model having 7-20-20-1 topology predicted the yield value with higher accuracy. Therefore, this two-hidden-layer topology was selected as the best model for estimating basil production of the regional greenhouses with similar conditions.

Sensitivity Analysis of Inputs Energy on Products Yield

The robustness and sensitivity of ANN models were determined by examining and comparing the output produced during the validation stage with the calculated values. A sensitivity analysis is the method of studying the behavior of a model, and assessing the significance of each input variable on the values of the output variable of the model. Sensitivity analysis provides insight into the usefulness of individual variables. By the help of this kind of analysis, it is possible to judge which inputs for modeling seed and grain corn parameters should be considered as the most significant and least significant ones during generation of the satisfactory MLP. To evaluate the predictive ability and validity of the developed models, a sensitivity analysis was performed with the best network for yield of

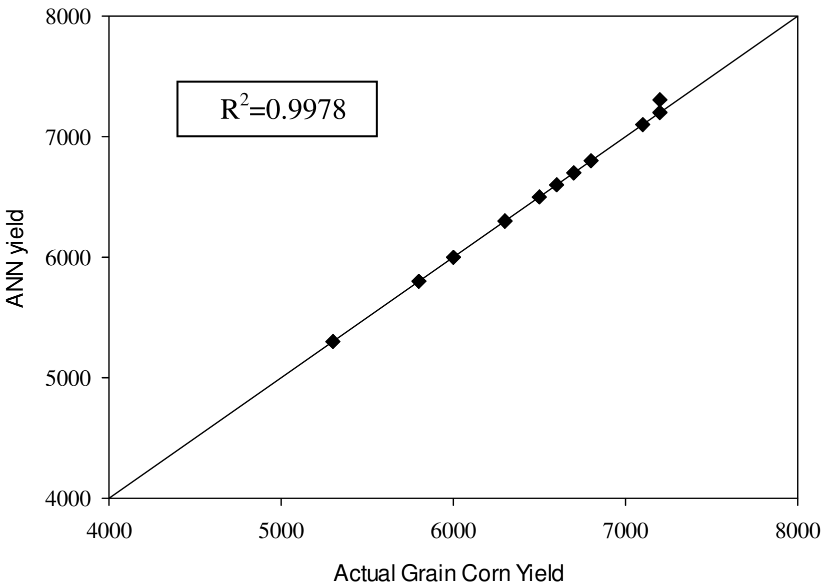

Figure 4. Regression graphs of ANN and actual output value of grain corn.

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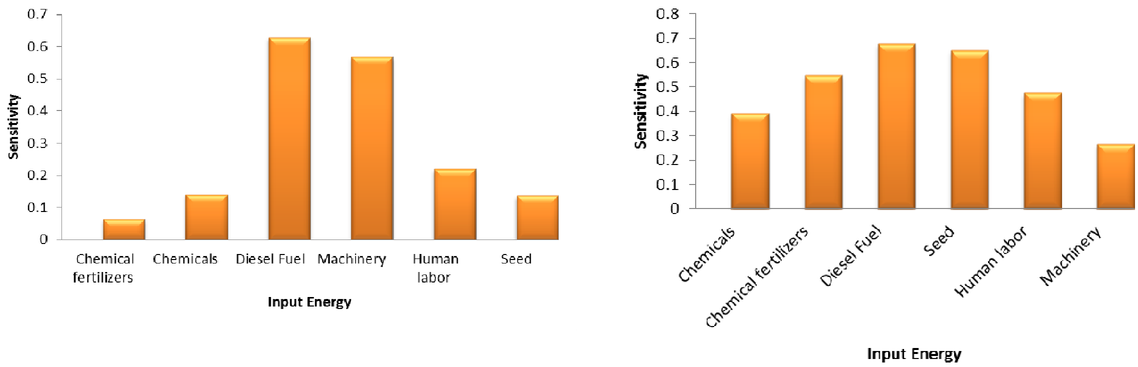

(a) (b)

Figure 5. Sensitivity analysis of various input energies on (a) seed corn (b) grain corn yield output.

both products (Tables 2 and 3, Figures 5 and 6). Results presented in Figures 5 and 6 show the impact of each input factor on the estimated yield of optimum MLP model. As can be seen in seed corn, diesel fuel and machinery, and in grain corn diesel fuel, seed consumption and chemical fertilizers had the greatest impact on product yield.

Dai *et al*. (2011) examined effect of soil moisture and salinity stress on sunflower yield by using ANN with MLP having 10 and 6 inputs. The standard deviations of 1.1 and 1.6 t ha^{-1} and R^2 of 0.84 and 0.8 were obtained, respectively. Results of the sensitivity analysis indicated that at each level of salinity stress, at different soil moisture, the yield will vary. At low and medium salinity, plant yield in squaring stage was down, and under high tension, it was more sensitive during aggregation stage. As a result, high moisture content of the soil at planting stage can compensate yield reduction due to salinity stress regardless of salinity levels. Pahlavan *et al.* (2012a) carried out sensitivity analysis of input parameters on basil production. Sensitivity analysis revealed that chemical fertilizer, farm yard manure (FYM), diesel fuel, and other chemicals energies had the highest sensitivity on output; while the sensitivity of electricity, human labor, and transportation energies was relatively low.

CONCLUSIONS

The objective of this study was to predict seed and grain corn yield production on the basis of input energies. In the present study, a back-propagation (BP) learning algorithm was chosen to predict the seed and grain corn production in northwest Iran. The input parameters chosen for the models were fertilizers, biocides, seed, human labor, diesel fuel, and machinery, while the seed and grain corn yield were the outputs. Accordingly, several ANN models were developed and evaluated and their prediction accuracy was evaluated using the quality parameters. The ANN models with 6-4-8-1 and 6-3-9-1 structures were the best models for predicting seed and grain corn yield, respectively. Model output value associated with the actual output had R^2 values of 0.9998 and 0.9978 for seed and grain corn, respectively. Multiple linear regression (MLR) analysis was conducted in order to compare the determined regression coefficients with ANN results. The R^2 values of MLR equations for seed and grain corn yield were 0.987 and 0.982, respectively. The sensitivity analysis of input parameters on output showed that, in seed corn, diesel fuel and machinery, and in grain corn, diesel

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fuel, seed consumption, and chemical fertilizers had the greatest sensitivity.

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شبکه عصبی مبتنی بر مدل سازی و آنالیز حساسیت نهاده‌های انرژی برای برآورد عملکرد ذرت بذری و دانه‌ای

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چکیده

در این بررسی، چندین شبکه‌های عصبی مصنوعی برای برآورد عملکرد ذرت بذری و دانه‌ای در پارس‌آباد مغان، ایران توسعه داده شد. داده‌ها به روش حضوری از ۱۴۴ ذرت‌کار در سال ۲۰۱۱ جمع آوری گردید. نسبت انرژی برای ذرت بذری به ترتیب ۰.۸۹ و۲.۶۵ محاسبه شد. چندین شبکه‌های عصبی مصنوعی پرسپترون چند لایه با ۶ نرون در لایه ورودی و یک تا سه لایه با نرون‌های متفاوت در هر لایه و یک نرون(عملکرد ذرت بذری و دانه‌ای)در لایه خروجی توسعه و آزمایش شد. نهاده‌های انرژی شامل کودهای شیمیایی، سموم، بذر، نیروی انسانی، سوخت دیزل و ماشین به عنوان متغیرهای لایه ورودی در نظر گرفته شدند. بهترین مدل برای پیش‌گویی عملکرد ذرت بذری و دانه‌ای به ترتیب دارای توپولوژی ۶-۴-۸-۱ و۶-۴-۹-۱ بودند. مدل‌های خروجی دارای ضریب تشخیص ۰.۹۹۹۸ و ۰.۹۹۷۸ بودند. مدل رگرسیونی دارای ضریب تشخیص ۰.۹۸۷ و۰.۹۸۲ بود. آنالیز حساسیت نشان داد که در تولید ذرت بذری، سوخت دیزل و ماشین و در ذرت دانه ای سوخت دیزل و بذر مصرفی بیشترین اثر را در عملکرد تولیدی دارند.

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