Surveying on energy pattern and application of neural network for predict energy consumption for wheat production in Iran

Mohamad Reza Moghimi[1*], Mohsen Pooya[2], Behzad Mohammadi Alasti[3] and Mehdi Abasgholipor Ghadim[3]

[1]*Young Researchers Club, Ghorveh Branch, Islamic Azad University, Ghorveh, Iran*
[2]*Department of Mechanization Engineering, University of Tehran, Science and Research, Khozestan, Iran*
[3]*Department of Agricultural Machinery, Bonab Branch, Islamic Azad University Bonab, Iran*

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ABSTRACT

The aim of this study was to examine energy use pattern and predict the output energy for dry wheat production in Gorve country, Kordestan province of Iran. The data used in this study were collected from farmers by using a face to face survey. The results revealed that wheat production consumed a total of 42.998 G J ha^{-1} and output was 97.935 G J ha^{-1}. Electricity has the highest share by 26.135 G J ha^{-1} followed by total fertilizers and diesel fuel. In this study, several direct and indirect factors have been identified to create an artificial neural networks (ANN) model to predict output energy for wheat production. The final model can predict output energy based on human labor, machinery, diesel fuel, chemical fertilizer, biocides, electricity and seed. The results of ANNs analyze showed that the (7-6-6-1)-MLP, namely, a network having six neurons in the first and second hidden layer was the best-suited model estimating the output energy. For this topology, MSE and R^2 were 0.003 and 94%, respectively. The sensitivity analysis of input parameters on output showed that total chemical fertilizer and seed had the highest and lowest sensitivity on output energy with 22% and 7%, respectively.

Key words: Artificial neural networks, Energy consumption, wheat production, Iran

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INTRODUCTION

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, chemicals, irrigation water, machinery etc. [11]. Efficient use of energy in agriculture is one of the principal requirements for sustainable agricultural production. Improving energy use efficiency is becoming increasingly important for combating rising energy costs, depletion of natural resources and environmental deterioration [6]. The development of energy efficient agricultural systems with low input energy compared to the output of food can reduce the greenhouse gas emissions from agricultural production systems [5]. The energy input–output analysis is usually made to determine the energy efficiency and environmental aspects. This analysis will determine how efficient the energy is used. Sensitivity analysis quantifies the sensitivity of a model's state variables to the parameters defining the model. It refers to changes in the response of each of the state variables which result from small changes in the parameter values. Sensitivity analysis is valuable because it identifies those parameters which have most influence on the response of the model. It is also an essential prerequisite to any parameter optimization exercise [4, 23]. In recent years, many researchers have investigated the energy use for agricultural crop production. Taki et al [26] studied the energy use patterns of cucumber production in Iran and found that the fertilizer application have the highest energy source in total inputs. Bahrami et al [3] studied the productive efficiency for wheat production in Iran by means of data envelopment analysis (DEA). An

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advantage of DEA is so that it does not require any prior assumptions on the underlying functional relationships between inputs and outputs. It is therefore a nonparametric approach. Mohammadi et al [13] used data envelopment analysis to analyze the energy efficiency for kiwifruit production in Iran. Results showed that 12.17% of input energy could be saved if the farmer follows the results recommended by this study. During the past 15 years there has been a substantial increase in the interest on artificial neural networks. The ANNs are good for some tasks while lacking in some others. Specifically, they are good for tasks involving incomplete data sets, fuzzy or incomplete information, and for highly complex and ill-defined problems, where humans usually decide on an intuitional basis. They can learn from examples, and are able to deal with non-linear problems. Furthermore, they exhibit robustness and fault tolerances. The tasks that ANNs cannot handle effectively are those requiring high accuracy and precision, as in logic and arithmetic. ANNs have been applied in a number of application areas. ANN has been successfully used in prediction of drying kinetics of seeds, vegetables, and fruits food process parameters [16]. For example, Erenturk and Erenturk [7] compared the use of genetic algorithm and ANN approaches to study the drying of carrots. They demonstrated that the proposed neural network model not only minimized the R^2 of the predicted results but also removed the predictive dependency on the mathematical models (Newton, Page, modified Page, Henderson-Pabis). Azadeh et al [1] presented an integrated genetic algorithm and ANN to estimate and predict electricity demand. The economic indicators were price, value added, and number of customers and consumption in the previous periods. Azadeh et al [1] also presented an ANN approach for annual electricity consumption in high energy consumption of industrial sectors based on a supervised multilayer perceptron (MLP). Rahman and Bala [22], employed ANNs to estimate jute production in Bangladesh. In this study an ANN model with six input variables including Julian day, solar radiation, maximum temperature, minimum temperature, rainfall, and type of biomass was applied to predict the desired variable (plant dry matter). Zangeneh et al [29] compared results of the application of parametric model and ANNs for assessing various economical indices (economical productivity, total costs of production and benefit to cost ratio) of potato crop in Hamadan province of Iran. Pahlavan et al [19] developed the various artificial neural networks models to estimate the production yield of greenhouse basil in Iran. Results showed, the ANN model having 7-20-20-1 topology can predict the yield value with higher accuracy.

Based on the literature, there has been no study on modeling wheat production with respect to input energies using ANNs. Thus, this study was devoted to the use of ANN models as an alternative approach for predicting output energy for wheat production in Gorve city, Kordestan province of Iran.

MATERIALS AND METHODS

This study was conducted in order to determine the amount of energy consumption for wheat production and optimize energy consumption for wheat in Gorve city in Kordestan province of Iran. The data was collected from 40 wheat growing farmers. For collecting the proper data covering the energy consumption pattern, appropriate questionnaires was designed and completed through face to face interviews. To obtain farmers sample volume Cochran formula is used [14]:

$$n = \frac{N(t.s)^2}{Nd^2 + (t.s)^2}$$

(1)

n = sample volume
N = population size
T = acceptable reliability which is obtained from T-student table (desired adjective is assumed normal).
S^2 = estimation variance of the trait studied
d = desired probable accuracy

An experimental survey is done in a small scale to obtain probable errors and to estimate approximate trait studied; as the above parameters initially have no determined trait variance. Initial sampling data was analyzed, and then data related to trait studied from the population was obtained approximately. Eventually, determined above parameters were put in the Cochran formula to obtain main sample volume. Thus, sample volume for 40 farmers of Gorve city was obtained.

To estimate the amount of energy used to produce field crops, it is necessary to determine energy equivalents for machinery manufacturing, depreciation, fuel consumption for operations, irrigation, labor, fertilizer, agricultural pesticides and seed, and their shares should be specified in total energy inputs. As matter of fact, the condition of field operations in different stages from tillage up to harvesting should be specified. The amounts of input were calculated per hectare and then, these input data were multiplied with the coefficient of energy equivalent. The previous studies were used to determine the energy equivalents coefficients. These sources are given in Table 1.

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Table 1 Energy equivalent of inputs and output in agricultural production

Inputs	Unit	Energy equivalents	Reference
A. Inputs			
1. Human Labor	h	1.96	(Mobtaker et al., 2010)
2. Machinery	h	64.80	(Kizilaslan, 2009)
3. Diesel fuel	l	56.31	(Heidari and Omid, 2011)
4. Total fertilizer	kg		
(a) Nitrogen	kg	66.14	(Rafiee et al., 2010)
(b) Phosphate (P_2O_5)	kg	12.44	(Mobtaker et al., 2010)
(c) Calcium	kg	8.8	(Pimentel, 1980)
(d) Farmyard manure	kg	0.3	(Heidari et al., 2011)
5. Biocides	kg	120	(Mobtaker et al., 2010)
6. Electricity	kWh	11.93	(Mobtaker et al., 2010)
7. Seed	kg	14.7	(Ozkan et al., 2007)
B. Output			
1. Grain wheat	kg	14.7	(Ozkan et al., 2007)
2. Straw	kg	9.25	(Tabatabaeefar et al. 2009)

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. Scientists have tried to mimic the operation of the human brain to solve various problems by using mathematical methods. They have found, and used, various networks to solve practical problems. Neural networks include a wide range of mathematical methods and artificial neural networks (ANN), the commonly used term to differentiate them from biological neural networks, have become one of the most important modeling method that have been used more than other modeling methods for complex input-output dependencies[18].

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 multilayer perceptron (MLP). The layers between the input layer and output layers are called hidden layers; 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 [9]. Each neuron in an MLP is connected to other neurons in a previous layer and the next layer through adaptable weights (*w*) which are the parameters of a network. Initially the values of these weights are set randomly. The networks use different learning methods to adjust these connection weights during the learning process. In the processing of inputs by the network, the signals (inputs) from a preceding layer are multiplied by the weights of their corresponding connections. Each neuron in the first layer (hidden layer) processes the weighted inputs through a transfer function to produce its output. The transfer functions may be a linear or a non-linear function. There are several transfer functions, such as Logistic, Hyperbolic tangent, Gussian, and Sine. 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. When this layer is the output layer, neuron output is the predicted output. In general, the dataset is randomly divided into training and validation sets. Training data is used during training when the weights are adjusted. Validation set is used for testing the generalization ability of the trained model on previously unseen data. The data consist of a set of inputs selected for representing a problem (input vector) and the corresponding output, an input vector Together with the corresponding output make a training vector [24].

MLPs are normally trained with Back Propagation (BP) algorithm. It is a general method to solving for weights and biases. 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. BP uses a Gradient Descent (GD) technique that is very stable when a small learning rate is used but has slow convergence properties. Several methods for speeding up BPs have been used, including adding a momentum term or using a variable learning rate. GD with a momentum (GDM) algorithm that is an improvement to the straight GD rule in the sense that a momentum term is used to avoide local minima, speeding up learning and stabilizing convergence, is used [19] Multiple layers of neurons with non-linear transfer functions allow the network to learn nonlinear and linear relationships between input and output parameters. Several MLP network architectures with one, two, three and four hidden layers have been trained and evaluated aiming at finding the one that could result in the best overall performance. In this work, the learning rules of Gradient Descent Momentum (GDM) and Levenberg-Marquardt (LM) were considered. No transfer function for the first layer was used. For the hidden layers the sigmoid functions were used, and for the output layer a linear transfer function was applied as desired for estimating problems.

A program was developed in Neuro Solutions 5.07 package [15], for the feed forward and back propagation network A 'N-fold cross validation' method was used that in this method data are randomly divided into two sets; training set (70% of all data) and cross validation set (the remaining 30% of all data) [19]. The neural network model is formed for output energy (Grain + straw) by using seven inputs.

Two statistical parameters were used for performance analysis. Mean square errors (MSE) and coefficient of determination (R^2) were computed to estimate the overall model performance. These are defined as:

$$MSE = \frac{\sum\limits_{i=1}^{n} \left(S_i - O_i \right)^2}{n} \tag{2}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N} (S_i - O_i)^2}{\sum_{i=1}^{N} O_i^2} \right) \tag{3}$$

Where i=1–N; N is the number of observations; S_i is the simulated values; O_i is the observed values [22].

RESULTS AND DISCUSSION

As it can be seen in the Table 2, 77.97 kg nitrogen, 34.98 kg Phosphate, 9.99 kg Calcium, 4587.50 kg of farm fertilizer, 72.95 l diesel fuel, 2.25 kg Biocides, 260.75 kg seed, 98.47 h human labor, 21.64 h machinery, 2190.77 Kwh electrical energy per hectare are used for the production of wheat in Gorve country in Iran. The average wheat output were found to be 7325 kg ha^{-1} in the enterprises that were analyzed. The energy equivalent of this is calculated as 97935.63MJha^{-1}. The highest energy input is provided by electrical. Some results have been reported in the literature that the energy input of chemical fertilizers has the biggest share of the total energy input in agricultural production [12, 27].

Table 2 Amounts of inputs, outputs and energy inputs and output in wheat production

Inputs (unit)	Quantity per unit area (ha)	Total energy equivalent (MJ ha^{-1})
A. Inputs		
1. Human labor (h)	98.47	193.00
2. Machinery (h)	21.64	1402.42
3. Diesel fuel (l)	72.95	4107.81
4. Total fertilizers (kg)	4710.44	7056.26
(a) Nitrogen (kg)	77.97	5156.94
(b) Phosphate (P$_2$O$_5$) (kg)	34.98	435.13
(c) Calcium (kg)	9.99	87.95
(d) Farmyard manure (kg)	4587.50	1376.25
5. Biocides (kg)	2.25	270.00
6. Electricity (m^3)	2190.77	26135.93
7. Seed (kg)	260.75	3833.03
The total energy input (MJ)		42998.44
B. Output		
1. Grain wheat	5537.50	81401.25
2. straw	1787.50	16534.38
Total energy output (MJ)		97935.63

In this research, various ANNs were designed and trained as one and two layers to find an optimal model prediction for the wheat output energy. For this purpose, Back propagation algorithm was chosen to build the prediction models. The results obtained from the 24 models and their characteristics are showed in Table 3. As indicated in Table 3, among the trained networks, the (7-6-6-1)-MLP, namely, a network having seven input variables, six neurons in the first and second hidden layer, and single output variable resulted in the best-suited model estimating the wheat output energy. For this topology, MSE and R^2 were 0.003 and 94%, respectively.

According to results of table 3, after (7-6-6-1)-MLP the most reliable models were: (7-9-1)-MLP model and (7-7-1)-MLP model respectively. R^2 and MSE for these models were: 92, 0.009 and 89, 0.014, respectively.

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Table 3 ANN models of wheat output energy prediction for different arrangement

Model	Numbers of Hidden layers	Neurons of hidden layers	Algorithm	MSE	R^2
MLP	1	5	Momentum	0.019	81
MLP	1	6	Momentum	0.022	79
MLP	**1**	**7**	**Momentum**	**0.014**	**89**
MLP	1	8	Momentum	0.057	68
MLP	1	9	Momentum	0.056	69
MLP	1	10	Momentum	0.064	58
MLP	1	5	LM	0.065	59
MLP	1	6	LM	0.117	47
MLP	1	7	LM	0.049	70
MLP	1	8	LM	0.121	45
MLP	**1**	**9**	**LM**	**0.009**	**92**
MLP	1	10	LM	0.245	44
MLP	2	5	Momentum	0.058	67
MLP	2	6	Momentum	0.059	66
MLP	2	7	Momentum	0.058	67
MLP	2	8	Momentum	0.056	69
MLP	2	9	Momentum	0.059	67
MLP	2	10	Momentum	0.055	70
MLP	2	5	LM	0.044	72
MLP	**2**	**6**	**LM**	**0.003**	**94**
MLP	2	7	LM	0.030	76
MLP	2	8	LM	0.045	71
MLP	2	9	LM	0.053	69
MLP	2	10	LM	0.029	75

According to the obtained results in Fig. 1, the share of each input item of developed MLP model on desired output (output energy) can be seen clearly. Sensitivity analysis provides insight into the usefulness of individual variables. With this kind of analysis it is possible to judge what parameters are the most significant and the least significant during generation of the satisfactory MLP [29]. It is evident that total fertilizer has the highest sensitivity on output (22%), followed by diesel fuel (21%). Also, the sensitivity of seed was relatively low. Pahlavan et al [19], reported that the chemical fertilizer energy had the highest sensitivity on output (basil production), followed by FYM (farm yard manure), diesel fuel and chemical poisons. Also, the sensitivity of electricity, human power and transportation energies were relatively low.
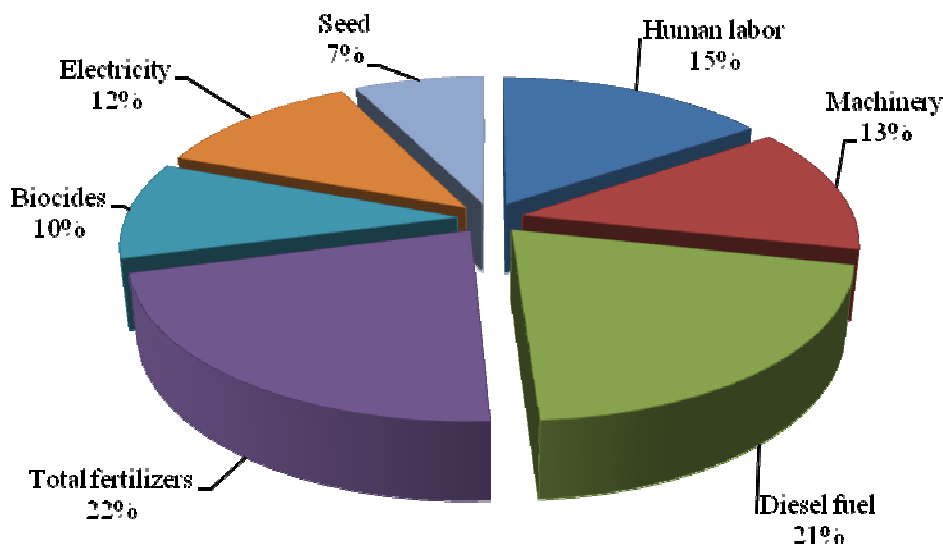

Fig.1. Sensitivity analysis of various input energies on dry wheat output energy

CONCLUSION

This paper shows the valuable application of Multilayer Feed Forward Network in modeling the input energies use in the wheat production in Gorve city in Kordestan province of Iran. Based on the results of this paper it can be stated that:

1. Wheat production consumed a total of 42998.44MJ ha^{-1}, and electricity has the highest share by 26135.93MJ ha^{-1}. Output energy was 97935.63MJ ha^{-1}. Management is a key factor to reduce energy use for agricultural production. Improving efficiency and using new methods and technologies can significantly enhance energy conservation on farms.

2. The (7-6-6-1)-MLP, namely, a network having seven input variables (Human labor, machinery, diesel fuel, chemical fertilizer, Biocides, Electricity and seed), six neurons in the first and second hidden layer, and single output variable (output energy) resulted in the best-suited model estimating the output energy for wheat production. For this topology, MSE and R^2 were 0.003 and 94%, respectively.

3. With regard to results of this research, it is suggested to use the same methodology to develop models for prediction of fuel consumption, CO_2 emission, input energy consumption and output yield for other agricultural production. It is possible to use the same database collected in this study for these investigations.

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