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Energy consumption and modeling of output energy with MLP Neural Network for dry wheat production in 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 Silakhor plain from Lorestan province of Iran. The data used in this study were collected from farmers by using a face to face survey. The results revealed that chemical fertilizer with seed and diesel fuel have consumed 57.93% and 36.58% of total energy, respectively. In this study, several direct and indirect factors have been identified to create an artificial neural networks (ANN) model to predict output energy for dry wheat production. The final model can predict output energy based on human power, machinery, diesel fuel, chemical fertilizer with seed and transportation. The results of ANNs analyze showed that the (5-10-10-1)-MLP, namely, a network having ten 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 0.029 and 90%, respectively. The sensitivity analysis of input parameters on output showed that chemical fertilizer with seed and human power had the highest and lowest sensitivity on output energy with 0.21and 0.03, respectively.

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 [1]. 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 [2]. 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 [3]. 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 [4-5].

In recent years, many researchers have investigated the energy use for agricultural crop production. Taki et al [6], 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 [7], studied the productive efficiency for wheat production in Iran by means of data envelopment analysis (DEA). An 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 [8] 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 [9]. For example, Erenturk and Erenturk [10] 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 [11] 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 [12] also presented an ANN

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approach for annual electricity consumption in high energy consumption of industrial sectors based on a supervised multilayer perceptron(MLP). Rahman and Bala [13] 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 [14] 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 [15] 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 dry 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 dry wheat production in Silakhor plain in Iran.

Materials and methods

Case study and data collection

This study was conducted in Silakhor plain of Lorestan province of Iran. Data were collected through personal interview method in a specially designed schedule for this study. The collected data belonged to the 2009/10 production year. Before collecting data, a pre-test survey was conducted by a group of randomly selected farmers. The required sample size was determined using simple random sampling method. The equation is as below [16]:

$$n = \frac{\sum N_h S_h}{N^2 D^2 + \sum N_h S_h^2} \quad \textbf{(1)}$$

where n is the required sample size; N is the number of total population; N_h is the number of the population in the h stratification; S_h is the standard deviation in the h stratification, S_h^2 is the variance in the h stratification, D^2 is equal to $\frac{d^2}{z^2}$; d is the precision, $(\bar{x} - \bar{X})$ (5%) is the permissible error and z is the reliability coefficient (1.96, which represents 95% reliability). Thus the sample size was found to be 120.

Energy equivalents of inputs and output

The inputs used in the production of dry wheat were specified in order to calculate the energy equivalences in the study. Inputs in dry wheat production were: human power, machinery, diesel fuel, chemical fertilizers with seed and transportation. The output was considered wheat. The energy equivalents given in Table 1 were used to calculate the input amounts.

Artificial neural network modeling

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 [25].

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

	Unit	**Energy equivalent (MJ Unit^{-1})**	**Reference**
Inputs			
1. Human power	H	1.96	[17]
2. Machinery	kg	64.8	[18]
3. Diesel fuel	L	47.8	[19]
4. Chemical	kg		-
Herbicides	kg	238	[20]
Fungicides	kg	216	[20]
Insecticides	kg	101.2	[20]
5. Fertilizer	kg		-
Nitrogen	kg	66.14	[21]
Phosphate	kg	12.44	[22]
Potassium	kg	11.15	[22]
6. Manure	tons	303.10	[23]
7. Water for	M^3	1.02	[24]
8. Seed (hybrid)	kg	25	[7]
Output	-	-	-
dry matter wheat	kg	14.7	[7]
Straw	kg	12.5	[7]

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 [26]. 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 [27]. A schematic diagram of typical multilayer feed forward neural network architecture is shown in Fig. 1.

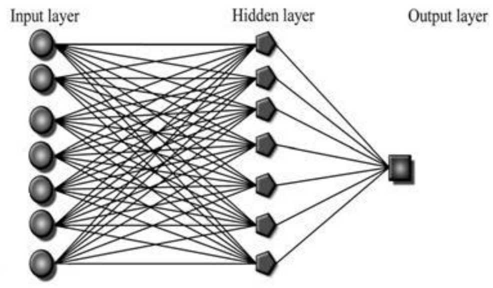

Figure 1. Schematic diagram of a multilayer feed forward neural network

Training, testing and validation of ANN

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 [15]. 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 [28] 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) [15]. The neural network model is formed for output energy (dry wheat production) by using five inputs (human power, machinery, diesel fuel, chemical fertilizer with seed and transportation), and one output (output energy).

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:

$$MSE = \frac{\sum_{i=1}^{n}\left(S_i - O_i\right)^2}{n} \qquad (2)$$

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

where i=1–N; N is the number of observations; S_i is the simulated values; O_i is the observed values [13].

Result and discussion

Energy use pattern

In Table 2, the physical inputs and their energy equivalents used in the production of dry wheat are given. Also, in Fig. 2, distribution of the anthropogenic energy input in the production of dry wheat is shown.

Table 2. The physical inputs used in the production of dry wheat and their energy equivalences

Input	Total energy equivalent (MJ)	Percentage
Transportation	120.18	1.05
Human power	97.80	0.86
Machinery	409.00	3.58
Chemical fertilizer with	6610.19	57.93
Diesel fuel	4172.80	36.58
Total energy input	11409.97	100
Output		
Dry wheat	43401	-

As it can be seen in Table 2, the energy used in the production of dry wheat consists of 1.05% transportation, 0.86% human power, 3.58% machinery, 57.93% chemical fertilizers with seed and 36.58% diesel fuel inputs. The highest energy input is provided by chemical fertilizers with seed. In a similar study [29], total energy inputs for wheat production in Fars Province of Iran were reported to be 38589 $MJha^{-1}$. The results showed that the most energy consuming input for wheat production in the different farms investigated was fertilizer and chemicals. Similar results were found in the literature that the highest energy item was diesel fuel in agricultural crops production [29-31].

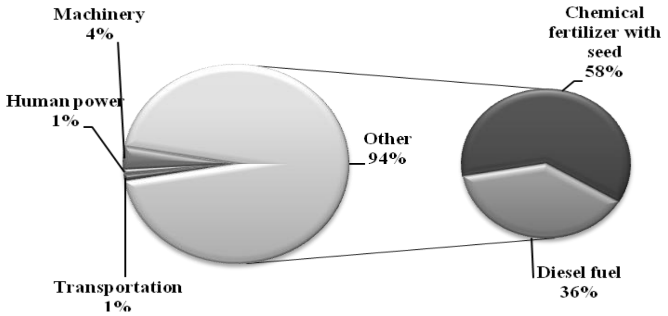

Fig 2. The anthropogenic energy input ratios in the production of dry wheat.

Evaluation of ANNs models

In this research, various ANNs were designed and trained as one and two layers to find an optimal model prediction for the dry 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 (5-10-10-1)-MLP, namely, a network having five input variables (human power, machinery, diesel fuel, chemical fertilizer with seed and transportation), 10 neurons in the first and second hidden layer, and single output variable (dry wheat output energy) resulted in the best-suited model estimating the dry wheat output energy. For this topology, MSE and R^2 were 0.029 and 90%, respectively.

According to results of table 3, after (5-10-10-1)-MLP the most reliable models were: (5-5-5-1)-MLP model and (5-7-1)-MLP model respectively. R^2 and MSE for these models were: 87, 0.044 and 86, 0.049, respectively.

Pahlavan et al [15] showed that the ANN model having (7-20-20-1) MLP topology with R^2 of 0.976 can predict the basil yield value with high accuracy. Zangeneh et al [32] reported that the ANN model with 13-4-1 configuration was the best model to estimate machinery energy ratio (MER) indicator for potato production in Iran. Rahman and Bala [13] reported that a model consisted of 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.

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

Model	Hidden layers	Neurons of hidden layers	Algorithm	MSE	R^2
MLP	1	5	Momentum	0.050	78
MLP	1	6	Momentum	0.107	78
MLP	1	7	Momentum	0.052	77
MLP	1	8	Momentum	0.057	74
MLP	1	9	Momentum	0.056	77
MLP	1	10	Momentum	0.064	60
MLP	1	5	LM	0.065	75
MLP	1	6	LM	0.117	72
MLP	1	7	LM	0.049	86
MLP	1	8	LM	0.121	84
MLP	1	9	LM	0.149	78
MLP	1	10	LM	0.245	71
MLP	2	5	Momentum	0.058	72
MLP	2	6	Momentum	0.059	72
MLP	2	7	Momentum	0.058	73
MLP	2	8	Momentum	0.056	71
MLP	2	9	Momentum	0.059	73
MLP	2	10	Momentum	0.055	85
MLP	2	5	LM	0.044	87
MLP	2	6	LM	0.054	84
MLP	2	7	LM	0.030	76
MLP	2	8	LM	0.045	84
MLP	2	9	LM	0.053	72
MLP	2	10	LM	0.029	90

Sensitivity analysis

In order to assess the predictive ability and validity of the developed models, a sensitivity analysis was performed using the best network selected (Fig. 3). The robustness of the model was determined by examining and comparing the output produced during the validation stage with the calculated values. The MLP model was trained by withdrawing each input item one at a time while not changing any of the other items for every pattern. According to the obtained results in Fig. 3, 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 [32]. It is evident that total fertilizer and seed had the highest sensitivity on output (0.21), followed by diesel fuel (0.12). Also, the sensitivity of human power was relatively low. Pahlavan et al [15] 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.

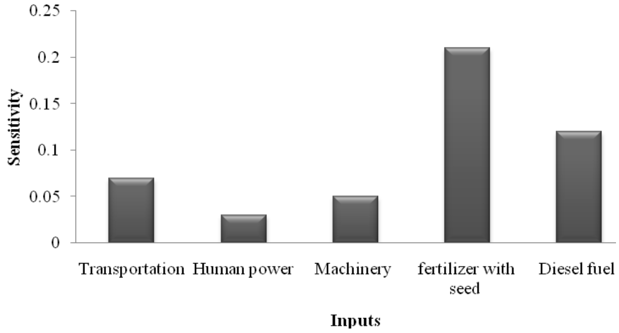

Fig 3. Sensitivity analysis of various input energies on dry wheat output energy

Conclusion

This paper shows the valuable application of Multilayer Feed Forward Network in modeling the input energies use in the dry wheat production in Lorestan Province of Iran.

Based on the results of this paper it can be stated that:

1. Dry wheat production consumed a total energy of 11409.97MJha^{-1}, which was mainly due to chemical fertilizer with seed (57.93% of total energy). The energy input of diesel fuel and machinery have the secondary and tertiary share within the total energy inputs. Energy output was calculated as 43401MJha^{-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 (5-10-10-1)-MLP, namely, a network having five input variables (human power, machinery, diesel fuel, chemical fertilizer with seed and transportation), 10 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 dry wheat production. For this topology, MSE and R^2 were 0.029 and 90%, 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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