# Energy consumption and modeling of output energy with multilayer feed-forward neural network for corn silage in Iran

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**Abstract:** In this study, various Artificial Neural Networks (ANNs) were developed to estimate the output energy for corn silage production in Esfahan province, Iran. For this purpose, the data on 65 corn silage production farms in the Esfahan province, were collected and analyzed. The results indicated that total energy input for corn silage production was about 83126 MJ $ha^{-1}$; machinery (with 38.8 %) and chemical fertilizer (with 24.5 %) were amongst the highest energy inputs for corn silage production. The developed ANN was a multilayer perceptron (MLP) with eight neurons in the input layer (human power, machinery, diesel fuel, chemical fertilizer, water for irrigation, seed, farm manure and pesticides), one, two, three, four and five hidden layer(s) of various numbers of neurons and one neuron (output energy) in the output layer. The results of ANNs analyze showed that the (8-5-5-1)-MLP, namely, a network having five neurons in the first and second hidden layer was the best-suited model estimating the corn silage output energy. For this topology, MAB, MAE, RMSE and $R^2$ were 0.109, 0.001, 0.0464 and 98%, respectively. The sensitivity analysis of input parameters on output showed that diesel fuel and seeds had the highest and lowest sensitivity on output energy with 0.0984 and 0.0386, respectively. The ANN approach appears to be a suitable method for modeling output energy, fuel consumption, $CO_2$ emission, yield, and energy consumption based on social and technical parameters. This method would open new doors to advances in agriculture and modeling.

**Keywords:** energy use, Artificial Neural Networks, sensitivity analysis, Iran

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## 1 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 energy sources, directly and indirectly, in the form of diesel, electricity, fertilizer, plant protection, chemical, irrigation water, machinery etc (Lianga, Fana and Wei, 2007). 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 (Dovì, Friedler, Huisingh and Klemes, 2009). 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, Halberg and Porter, 2001). 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 models state variable 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

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analysis is valuable because it identifies those parameters which have the most influence on the response of the model. It is also an essential prerequisite to any parameter optimization exercise (Richter, Acutis, Trevisiol, Latir and Confalonieri, 2010).

In recent years, many researchers have been investigated the energy use for agricultural crop production. Taki, Ajabshirchi and Mahmoudi, (2012a) 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, Taki and Monjezi, (2011) studied the productive efficiency for wheat production in Iran by means of data envelopment analysis (DEA). An advantage of DEA is that it does not require any prior assumptions on the underlying functional relationships between inputs and outputs. It is therefore a nonparametric approach. Franzluebbers and Francis (1995) investigated the energy requirements for maize and sorghum management systems in Nebraska, USA. They concluded that energy ratio decreased with N fertilizer application in all management systems, except with cereal as previous crop and low initially available N. In Turkey, the energy use patterns of wheat, cotton, maize, sesame was studied and found that the fertilizer application have the highest energy source in total inputs with the share of 52.7% in maize production (Canakci, Topakci, Akinci and Ozmerzi, 2005).

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. 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 (ANNs), 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 (Pachepsky, Timlin and Varallyay, 1996).

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 tolerance. 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 (Omid, Baharlooei and Ahmadi, 2009). For example, Erenturk and Erenturk (2006) 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, Ghaderi, Tarverdian and Saberi, (2007) 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, Ghaderi and Sohrabkhani, (2008) 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 (2010) 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, Omid and Akram, (2011) 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, Omid and Akram, (2012) 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 corn silage 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 corn silage in Esfahan province of Iran.

## 2 Materials and methods

### 2.1 Case study and data collection

This study was conducted in Esfahan province of Iran. This province is located within 30° 42' and 34° 30' north latitude and 49° 36' and 55° 32' east longitude. 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 (Mousavi–Avval, Rafiee and Mohammadi, 2011):

$$n = \sum N_h S_h \Big/ N^2 D^2 + \sum N_h S_h^2 \tag{1}$$

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 65. Consequently, based on the number of corn silage producers in each village the 65 farmers from the population were randomly selected.

### 2.2 Energy equivalents of inputs and output

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

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

| | Unit | Energy equivalent /MJ Unit$^{-1}$ | Reference |
|---|---|---|---|
| Inputs | | | |
| Human power | H | 1.96 | Singh et al., 2000 |
| Machinery | kg | 64.8 | Mikkola and Ahokas, 2010 |
| Diesel fuel | L | 47.8 | Singh et al., 2000 |
| Pesticides | kg | | |
| Herbicides | | 238 | Erdal et al., 2007 |
| Fungicides | | 216 | Erdal et al., 2007 |
| Insecticides | | 101.2 | Erdal et al., 2007 |
| Fertilizer | kg | | |
| Nitrogen | | 66.14 | Çetin and Vardar, 2008 |
| Phosphate | | 12.44 | Shrestha, 1998 |
| Potassium | | 11.15 | Shrestha, 1998 |
| Manure | ton | 303.10 | Mohammadi et al., 2010 |
| Water for irrigation | $m^3$ | 1.02 | Rafiee et al., 2010 |
| Seed (hybrid) | kg | 100 | Pishgar Komleh et al., 2011 |
| Output | | | |
| Dry matter corn silage | kg | 8 | Pishgar Komleh et al., 2011 |

The energy equivalent of human power is the muscle power used in field operations of crop production. Pesticides and chemical fertilizers energy equivalents means the energy consumption for producing, packing and distributing the materials and they are given on an active ingredient basis. Farmyard manure is regarded as a source of nutrients, so the energy equivalent of farmyard manure equates with that of mineral fertilizer equivalents corresponding to the fertilization effect of the applied manure. Also, the energy sequestered in diesel fuel mean their heating value (Enthalpy) and the energy needed to make their energy available directly to the farmers. Moreover, the seed energy is the energy used in the production of a crop and the grain energy is the gross energy content determined from laboratory bomb calorimeter tests (Kitani, 1999). The energy equivalent of water for irrigation input means indirect energy of irrigation consist of the energy consumed for manufacturing the materials for the dams, canals, pipes, pumps, and equipment as well as the energy for constructing the works and building the on-farm irrigation (Mousavi–Avval, Rafiee and Mohammadi, 2011). For calculating the embodied energy in agricultural machinery it was assumed that the energy consumed for the production of the tractors and agricultural machinery be depreciated during their economical life time (Beheshti Tabar, Keyhani and Rafiee, 2010); therefore, the machinery energy input was calculated using the following Equation (2) (Mousavi–Avval, Rafiee and Mohammadi, 2011):

$$ME = \frac{G \times MP \times t}{t} \tag{2}$$

where, *ME* is the machinery energy per unit area (MJ ha$^{-1}$); *G* is the machine mass (kg); *MP* is the production energy of machine (MJ kg$^{-1}$); *t* is the time that machine used per unit area (h ha$^{-1}$) and *T* is the economic life time of machine (h).

### 2.3 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). 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 (Kalogirou, 2001). 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. A schematic diagram of typical multilayer feed forward neural network architecture is shown in Figure 1.

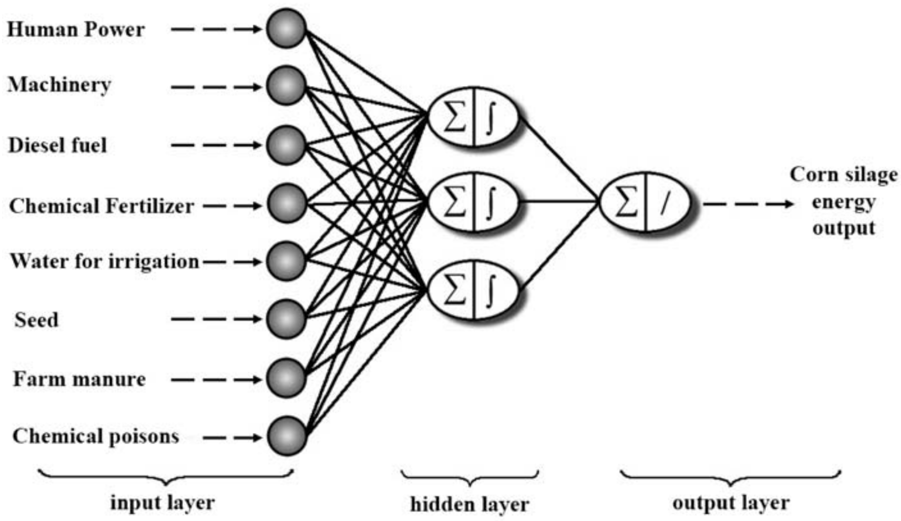


Figure 1 Schematic diagram of a multilayer feed forward neural network

### 2.4 Training, testing and validation of ANN

MLPs are normally trained with Back Propagation (BP) algorithm. It is a general method for iteratively 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 avoiding local minima, speeding up learning and stabilizing convergence, is used (Pahlavan, Omid and Akram, 2012). 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 (2011) for the feed forward and back propagation network. We used an N-fold cross validation method 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) (Pahlavan, Omid and Akram, 2012). The neural network model is formed for output energy (corn silage production) by using eight inputs (human power, machinery, diesel fuel, chemical fertilizer, water for irrigation, seed, farm manure and pesticides), and one output (output energy).

Four statistical parameters were used for performance analysis. Mean absolute bias error (*MAB*), root mean square error (*RMSE*), mean absolute error (MAE) and coefficient of determination ($R^2$) were computed to estimate the overall model performance. These are defined as:

$$MAB = \frac{\sum_{i=1}^{N}(S_i - O_i)}{N} \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}|(S_i - O_i)|}{N}} \quad (4)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|(S_i - O_i)| \quad (5)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N}(S_i - O_i)^2}{\sum_{i=1}^{N}O_i^2}\right) \quad (6)$$

where, $i$=1–$N$; $N$ is the number of observations; $S_i$ is the simulated values; $O_i$ is the observed values. $R^2$ and *RMSE* are the two most commonly used statistical parameters, which represent the degree of explanation and the average difference between estimated and observed values. Values of $R^2$ close to 1 with small values for the error terms are desirable (Rahman and Bala, 2010).

## 3 Result and discussion

### 3.1 Energy use pattern

In Table 2, the physical inputs and their energy equivalences used in the production of corn silage are given. Also, in Figure 2, distribution of the anthropogenic energy input ratios in the production of corn silage are given.

**Table 2 Physical inputs used in the production of corn silage and their energy equivalences**

| Input (unit) | Quantity per unit area/ha$^{-1}$ | Total energy equivalent/MJ | Percentage |
|---|---|---|---|
| 1. Pesticides (kg) | 30 | 6460 | 7.77 |
| Herbicides (kg) | 20 | 4760 | |
| Fungicides (kg) | 6 | 1296 | |
| Insecticides (kg) | 4 | 404.8 | |
| 2. Human power (h) | 871 | 1707 | 2.04 |
| 3. Machinery (kg) | 497 | 32251 | 38.8 |
| 4.Chemical Fertilizer (kg) | 550 | 20073 | 24.5 |
| Nitrogen fertilizer (kg) | 250 | 16535 | |
| Phosphate (kg) | 150 | 1866 | |
| Potassium (kg) | 150 | 1672 | |
| 5. Manure (ton) | 10 | 3031 | 3.64 |
| 6. Seeds (kg) | 32.1 | 3210 | 3.85 |
| 7. Diesel fuel (L) | 207 | 9862 | 11.85 |
| 8. Water for irrigation (m$^3$) | 6403 | 6532 | 7.85 |
| Total energy input (MJ) | - | 83126 | 100 |
| Corn silage (kg ha$^{-1}$) | 35000 | 280000 | |

As it can be seen in the Table 2, 250 kg nitrogen, 150 kg Phosphate, 150 kg potassium, 10 t of farm fertilizer, 207 L diesel fuel, 6,403 m$^3$ water, 30 kg pesticides, 871 h human power and 497 h machinery per hectare are used for the production of corn silage in Esfahan province of Iran. The average corn silage output were found to be 35,000 kg ha$^{-1}$ in the enterprises that were analyzed. The energy equivalent of this is calculated as 280,000 MJ ha$^{-1}$. It can be seen in Table 2 that the energy used in the production of corn silage consists of 7.77% pesticides, 2.04% human power, 38.8% machinery, 24.5% chemical fertilizers, 11.85% diesel fuel, 3.64% manure and 7.85% water inputs. The highest energy input is provided by machinery. The results were similar to Pishgar Komleh, Keyhani, Rafiee and Sefeedpary, (2011) where machinery and chemical fertilizer were major energy inputs. Phipps, Pain and

Mulvany, (1976) reported that the total energy input for corn silage production was to be 21,400 MJ ha$^{-1}$. In a Italy research, the energy input in maize production for conservation farming (CF) and organic farming (OF) systems were reported to be 46,900 and 25,890 MJ ha$^{-1}$, respectively (Sartori et al., 2005). Similar results have been reported in the literature that the energy input of chemical fertilizers and diesel fuel has the biggest share of the total energy input in agricultural crops production (Nassiri and Singh, 2009; Mohammadi and Omid, 2010). Consequently, Börjesson and Tufvesson (2011) reported that chemical fertilizers and diesel fuel were the main energy consuming inputs in wheat, sugar beet, canola, ley crops, maize and willow productions.

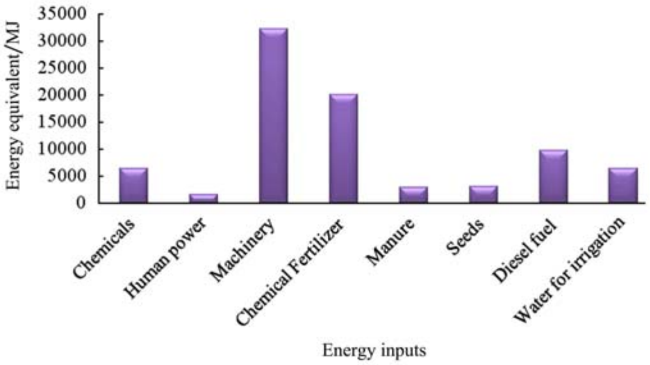


Figure 2 Anthropogenic energy input ratios in the production of corn silage

### 3.2 Evaluation of ANNs models

In this research, Various ANNs were designed and trained as one, two, three, four and five layers to find an optimal model prediction for the corn silage output energy. For this purpose, back propagation algorithm was chosen to build the prediction models. The results obtained from the 25 models and their characteristics are showed in Table 3. As indicated in Table 3, among the trained networks, the (8-5-5-1)-MLP, namely, a network having eight input variables (human power, machinery, diesel fuel, chemical fertilizer, water for irrigation, seed, farm manure and pesticides), five neurons in the first and second hidden layer, and single output variable (corn silage output energy) resulted in the best-suited model estimating the corn silage output energy. For this topology, *MAB*, *MAE* and $R^2$ were 0.109, 0.001 and 98%, respectively.

According to results of Table 3, after (8-5-5-1)-MLP the most reliable models were respectively: (8-10-10-10-10-1)-MLP model and (8-25-25-1)-MLP model. $R^2$, *MAB* and *MAE* for these models were: 97, 0.162, 0.006 and 96, 0.175 and 0.031, respectively. Figure 3 shows the average values of RMSE for the each ANNs of models. The difference between values predicted by (8-5-5-1)-MLP and real value of data is shown in Figure 4.

**Table 3 ANN models of corn silage prediction for different arrangement**

| Model | Hidden layers | Neurons of hidden layers | *MAB* | *MAE* | $R^2$/% |
|---|---|---|---|---|---|
| MLP | 1 | 5 | 0.245 | 0.005 | 69 |
| MLP | 1 | 10 | 0.176 | 0.002 | 72 |
| MLP | 1 | 15 | 0.320 | 0.005 | 79 |
| MLP | 1 | 20 | 0.221 | 0.038 | 68 |
| MLP | 1 | 25 | 0.119 | 0.053 | 83 |
| MLP | 2 | 5 | 0.109 | 0.001 | 98 |
| MLP | 2 | 10 | 0.227 | 0.006 | 88 |
| MLP | 2 | 15 | 0.261 | 0.008 | 90 |
| MLP | 2 | 20 | 0.225 | 0.037 | 77 |
| MLP | 2 | 25 | 0.175 | 0.031 | 96 |
| MLP | 3 | 5 | 0.198 | 0.035 | 66 |
| MLP | 3 | 10 | 0.336 | 0.028 | 92 |
| MLP | 3 | 15 | 0.230 | 0.058 | 93 |
| MLP | 3 | 20 | 0.271 | 0.054 | 45 |
| MLP | 3 | 25 | 0.288 | 0.056 | 55 |
| MLP | 4 | 5 | 0.225 | 0.064 | 64 |
| MLP | 4 | 10 | 0.162 | 0.006 | 97 |
| MLP | 4 | 15 | 0.261 | 0.059 | 66 |
| MLP | 4 | 20 | 0.220 | 0.068 | 82 |
| MLP | 4 | 25 | 0.177 | 0.062 | 80 |
| MLP | 5 | 5 | 0.169 | 0.042 | 71 |
| MLP | 5 | 10 | 0.331 | 0.051 | 79 |
| MLP | 5 | 15 | 0.229 | 0.054 | 94 |
| MLP | 5 | 20 | 0.291 | 0.032 | 59 |
| MLP | 5 | 25 | 0.267 | 0.054 | 62 |

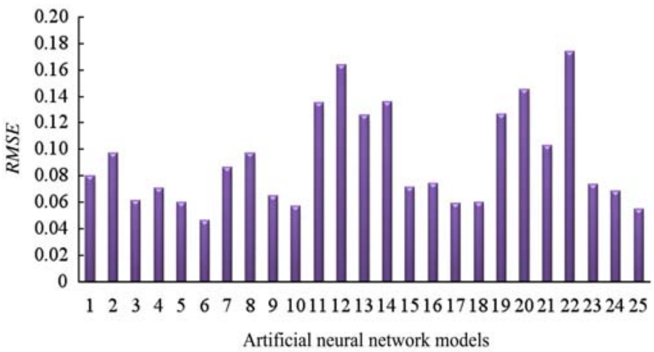


Figure 3 RMSE between the ANN predicted and actual outputs of corn silage

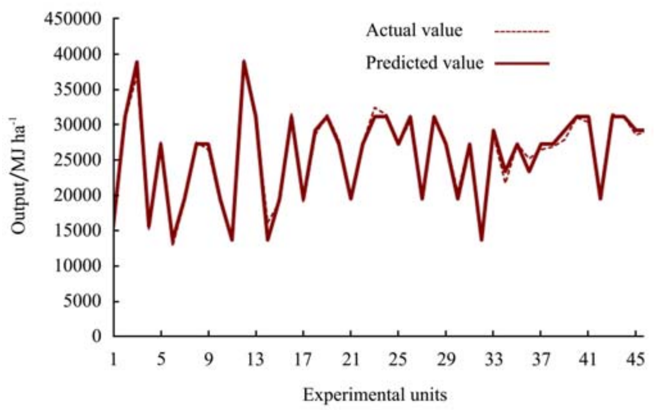


Figure 4 Predicted and actual network for MLP with 8-5-5-1 topology

Pahlavan et al. (2012) 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. Rahman and Bala (2010) reported that a model consisted of an input layer with six neurons, two hidden layers with nine and five neurons and one neuron in the output layer was the best model for predicting jute production in Bangladesh. Simulation models have been developed for predicting plant yield under differing environmental conditions (Jones, Dayan and Allen, 1991; Chalabi, Biro, Bailey, Aikman and Cockshull, 2002). These models are often based on estimates of physiological processes such as photosynthesis, respiration, and carbon partitioning to fruit. Models of yield have also been constructed using neural networks (Lin and Hill, 2008). One 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, Hill, Helmer and Edwards, 2011).

### 3.3 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 (Figure 5). 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 Figure5, 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 (Zangeneh, Omid and Akram, 2010). It is evident that diesel fuel had the highest sensitivity on output (0.0984), followed by machinery (0.0901). Also, the sensitivity of seeds was relatively low. Taki, Ajabshirchi and Mahmoudi, (2012b) reported that the human power energy had the highest sensitivity on output (wheat production), followed by diesel fuel and pesticides. Also, the sensitivity of irrigation energy was relatively low.

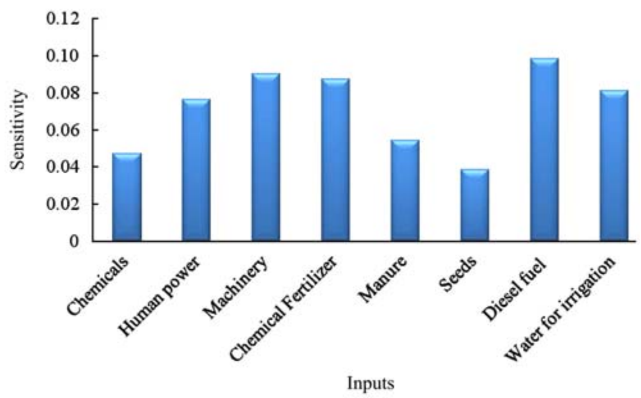


Figure 5 Sensitivity analysis of various input energies on corn silage output energy

## 4 Conclusion

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

1) Corn silage production consumed a total energy of 83,126 MJ ha$^{-1}$, which was mainly due to machinery (38.8% of total energy). The energy input of chemical fertilizer and diesel fuel have the secondary and tertiary share within the total energy inputs. Output energy was calculated as 280,000 MJ ha$^{-1}$.

2) The (8-5-5-1)-MLP, namely, a network having eight input variables (human power, machinery, diesel fuel, chemical fertilizer, water for irrigation, seed, farm manure and pesticides), five neurons in the first and second hidden layer, and single output variable (corn silage output energy) resulted in the best-suited model

estimating the corn silage output energy. For this topology, *MAB*, *MAE*, *RMSE* and $R^2$ were 0.109, 0.001, 0.0464 and 98%, respectively.

3) Using the same methodology can develop models to predict fuel consumption, $CO_2$ emission, and other agricultural production (yield). It is possible to use the same database collected in this study for these investigations. Modeling fuel consumption, $CO_2$ emission, yield, and energy consumption based on social and technical parameters would open new doors to advances in agriculture and modeling.

4) ANN models can estimate energy use of all products on each farm to find the most energy efficient combination of different agricultural products (rotation) and agricultural operations under different conditions. To develop this complex model, several farms must be involved and their production and operation must be investigated carefully. Establishing an international protocol to estimate energy use in agricultural production would be a great step toward sharing and comparing different results. Estimating national energy consumption for different agricultural production and comparing results from other countries would be helpful for the adoption of different farming systems globally. Additionally, this comparison can find the most important barriers to reduce energy use on farms in each country and globally.

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