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# Prediction of Orange Orchards Output in Northern Region of Iran using Artificial Neural Network Model

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**ABSTRACT**

In this study the energy consumption of orange orchards was surveyed and various Artificial Neural Networks (ANNs) developed to estimate the farmer's production in the Sari region as a case study. The data were collected using a face-to-face questionnaire method from 86 farmers in the Sari region. The results indicated that the total amount of energy input and output were 54284.8 and 59223.4 MJ $ha^{-1}$, respectively. Among all inputs involved, diesel fuel had the highest energy values per hectare. Also, energy efficiency, energy productivity and net energy were calculated as 1.09, 0.57 kg $MJ^{-1}$ and 4938.5 MJ $ha^{-1}$, respectively. Performance of developed ANN models were evaluated using the coefficient of determination ($R^2$), mean absolute error (MAE) and root mean squared error (RMSE). The resulting tests showed that best performance was achieved by a momentum training algorithm resulting in $R^2$=0.84, and MAE= 0.32 and RMSE=0.38 with 8-4-1 topology. Additionally, sensitivity analysis revealed that fertilizer and electricity energy had the highest and the lowest sensitivity on output, respectively.



## Introduction

Energy use in agriculture has developed in response to increased population, limited supply of arable land and desire for an increasing standard of living (Mohammadshirazi et al., 2012). The agricultural sector has become increasingly dependent on energy resources, such as electricity, fossil fuels, chemicals and fertilizers, largely due to relatively low prices of them especially in developing countries; however, intensive use of energy causes problems threatening public health and environment (Singh et al., 2004). Efficient use of energy is one of the essential requirements for sustainability of agricultural development energy has a key role in economic and social development but there is a general lack of rural energy development policies that focus on agriculture (Rafiee et al., 2010). Artificial Neural Networks (ANNs) are known as mathematical techniques to accomplish a variety of tasks. Using ANNs among investigators have not long background and started from 1980s (Azadeh et al. 2008). ANNs have been developed as a generalization of mathematical models of human neural biological system and consists of an inter-connection of a number of neurons and has a natural propensity for storing experiential knowledge and making it available for use (Mohammadi et al., 2009). Due to a neural network's ability to model complex non-linear systems in a flexible and adaptive manner, ANNs are being used more and more at present (Jebaraj and Iniyan, 2006). Due to ANNs special abilities such as the ability to find internal representations of interrelations within raw data, identify the complex interactions between independent variables without the need for complex functional models to describe the relationships between dependent and independent variables, intuitiveness to learn by example rather than by following programmed rules and its relative simplicity of building and training ANNs, encouraged their application to the task of prediction (Sefeedpari et al., 2012). Today, ANNs can be configured in various arrangements to perform a range of tasks including forecasting, classification, pattern recognition, data mining and process modeling (Azadeh et al., 2008). Consequently In recent years ANN's ability to forecast has propelled researchers to investigate agricultural operations (Avami and Boroushaki, 2011). Review the literate shows that many studies had been done using ANNs such as: Mohammadi et al. (2010) for kiwifruit production, Mousavi-Avval et al (2011) for canola production, Houshyar et al. (2010) for wheat production, Taki et al. (2012) for wheat production, Mobtaker et al. (2010) for barley production and Shakibai et al. (2009) for agricultural energy consumption in Iran and Singh et al. (2000) for cotton production in India. Many researchers have studied energy consumption patterns for various crops and situations because of the importance of energy consumption and its relationship to agricultural productivity. Based on the literature there was no study to predict the orange production using ANNs model. This study was done to fine an accurate estimation of orange production on the basis of energy inputs in Sari region of Iran.

## Materials And Methods

### Data collection and case study

In this study, orange growers of Sari region located in the northern part of Iran within 35° 58 and 36° 50 north latitude and 52° 56 and 53° 59 east longitude were surveyed during the 2011/2012 production year. Data were collected using the personal interview method in a specially designed schedule. The size of each sample was determined using Equation. (1) (Kizilaslan, 2009):

$$n = \frac{N(S\times T)^2}{(N-1)d^2+(S\times T)^2} \quad (1)$$

Where $n$ is the required sample size; $N$ is the number of holdings in the target population; $S$ is the standard deviation; $T$ is the t-value at a 95% confidence limit (1.96); and $d$ is the acceptable

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error (permissible error 5%). Thus the calculated sample size in this study was determined to be 86 orange farms. Consequently, based on this number, 86 orange farmers in Sari region were randomly selected. In order to estimate orange production in the region the quantity of human power, machinery, diesel fuel, chemicals, fertilizers, farmyard manure, water for irrigation and electricity as input sources per hectare were defined. Also, orange production yield was used to calculate output energy. To calculating the embodied energy in agricultural machinery it was assumed that the energy consumed for the production of the tractors and agricultural machinery is depreciated during their economic life time (Mousavi-Avval et al., 2011b). Therefore, the machinery energy input was calculated using the Equation (2) (Gezer et al., 2003).

$$\mathbf{ME} = (\mathbf{G} \times \mathbf{Mp} \ \times \mathbf{t})/\mathbf{T} \qquad (2)$$

Where *ME* is the machinery energy per unit area ($MJha^{-1}$); *G* is the machine mass (kg), *Mp* is the production energy of machine ($MJkg^{-1}$); *t* is the time that machine used per unit area ($hha^{-1}$) and *T* is the economic life time of machine (h).The data were calculated for 1 hectare was converted into energy units and expressed in MJ $ha^{-1}$. The energy equivalents of all 8 input sources were used to calculate the input amounts and are given in Table 1. Additionally, the energy ratio, energy productivity, and net energy are defined by the following equations (Mohammadi and Omid, 2010; Qasemi Kordkheili et al., 2013).

$$\text{Energy Ratio} = \frac{\text{Energy output } (\text{MJha}^{-1})}{\text{Energy input } (\text{MJha}^{-1})} \qquad (3)$$

$$\text{Energy Productivity} = \frac{\textbf{Orange output } (\textbf{kgha}^{-1})}{\textbf{Energy input } (\textbf{MJha}^{-1})} \qquad (4)$$

$$\text{Net energy} = \text{Energy output } (\text{MJha}^{-1}) - \text{Energy input } (\text{MJha}^{-1}) \qquad (5)$$

Consequently, based on the energy equivalents of the energy sources table 1 and using equations 3-5, these indices are calculated.

**Artificial Neural Networks**

ANNs are a computational procedure and free-model intelligent dynamic system, the function of which is inspired by the biological nervous system. Generally, ANNs are simply mathematical techniques designed to accomplish a variety of tasks. ANNs are inspired by human brain functionality and structure, which can be represented as a network of densely interconnected elements called neurons (Zangeneh et al., 2011). A biological neuron is shown in Figure 1 (Kalogirou, 2007).

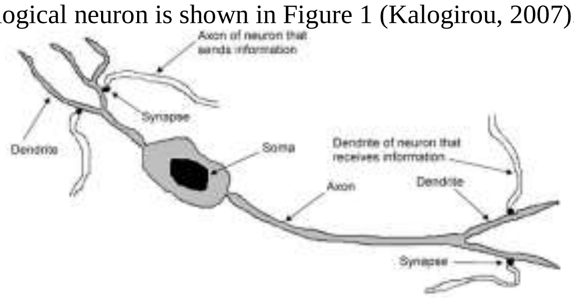


**Figure. 1. A simplified model of a biological neuron.**

Main advantage of ANNs over statistical methods is that they require no assumptions about the form of a fitting function. Instead, the network is trained with experimental data to find the relationship; so they are becoming very popular estimating tools and are known to be efficient and less time consuming in modeling of complex systems compared to other mathematical models such as regression (Pahlavan et al., 2012). The ANNs structure consists of an input layer, includes one or more hidden layers and an output layer. The fundamental processing element of it is neurons, which are placed in successive layers with three components: the input layer, the hidden layer and the output layer. The data enters the network from the input layer to the output layer through the hidden layer. The input nodes are the previous behindhand observations, while the output supplies the predicted for the future value. Additionally, the hidden nodes with appropriate nonlinear transfer functions are used to process the information received by the input nodes. The model can be written as follow (Azadeh et al., 2008):

$$y_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-i} + \beta_{0j}\right) + \varepsilon_t \quad , \ j = 0, \ 1, \ldots, \ n$$

and $i = 0, 1, \ldots, m$ (6)

Where *m* is the number of input nodes, *n* is the number of hidden nodes, $\alpha_j$ is the vector of weights from the hidden to output nodes and $\beta_{ij}$ is the weights from the input to hidden nodes. Also, $\alpha_0$ and $\beta_{0j}$ represent weights of arcs leading from the bias terms which have values always equal to 1 and *f* is a sigmoid transfer function (Shakibai et al., 2009). In order not to saturate the condition of the neurons, data normalization is required. If neurons get saturated, then the changes in the input value will produce a very small change or no change at all in the output value. For this reason, data must be normalized before being presented to the ANN (Taki et al., 2012). Data normalization is necessary to get better output results and not saturate the conditions of the neuron because ANNs cannot be trained with the raw data. Data mining and signal processing are used for data preprocessing. Data normalization compresses the range of the training data. Normalization was carried out using Equation. (7) (Taki et al., 2012):

$$X_n = \frac{X - \bar{X}}{S} \qquad (7)$$

where $X_n$ is the value of the normalized data, $\bar{X}$ and *S* are mean and standard deviation of the entire data set, respectively.

In this study several networks were examined using Neuro Solutions 6 for training and testing of neural network. Multilayer perceptrons (MLP), radial basis function (RBF), general feed forward network (GFFN), and probabilistic neural network (PNN) were examined by changing the number of hidden layers, neurons and training algorithms. Also, two different algorithms, Momentum and Levenberg Marquart (LM) were used as training algorithms. Collected data was subdivided into three groups: 60% was allocated to training, 15% for cross-validation and 25% for the test. This corresponds to 51 orchards for training, 13 orchards for cross validation and 22 orchards for testing. The performance quantification of ANN models for estimating the desired output of orange production investigated using the correlation coefficient (r), root mean square error (RMSE) and mean absolute error (MAE) between the predicted and actual values. The *RMSE* is a measure of how close the ANN predicted yield is to the one based on predicted results. These parameters were calculated using the following equations (Rahman and Bala, 2010):

$$r = \sqrt{1 - \left( \frac{\sum_{i=1}^{n} (\mathbf{P}_i - \mathbf{A}_i)^2}{\sum_{i=1}^{n} \mathbf{A}_i^2} \right)} \qquad (8)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - A_i)^2} \qquad (9)$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| (P_i - A_i) \right| \qquad (10)$$

Where $P_i$ and $A_i$ are predicted and actual yield for the $i^{th}$ farmer, respectively.

## Results And Discussion

### Analysis of input-output energy use in orange production

The physical input sources and their energy equivalents used in the production of orange are presented in Table 2.

Table-2 Energy input sources, output and their energy equivalents for orange production.

As can be seen in Table- 2, the total amount of energy input and output are 54284.8 and 59223.4 MJ ha$^{-1}$, respectively. In the other words, the average orange yield was 31270.2 kg ha$^{-1}$. Farmers used, in total, 651.7 kg of fertilizers, 15891.1 tons of farmyard manure and 21.04 kg of chemical agents per hectare. They also used 1342.3 h of human power, 281.9 L of diesel fuel, 11835.5 m$^3$ of water for irrigation and 363.9 kWh of electrical energy per hectare for the production of oranges in Mazandaran province. The large amount of water usage in this area is the result of farmers irrigating on average 8-10 times during each production year. Many famers use diesel motor pumps to irrigate orchards but the remaining farmers use electrical motor pumps with the result that electricity is consumed only for irrigation purposes. Drop and flood irrigating were the two irrigating system used. 54 orchards were irrigated with a flooding system that caused water wastage, while remaining orchards were equipped with a drop irrigation system. Drop irrigating system has high fixed costs. In calculation of machinery energy 50 h usage of machines in average per hectare and economic life were considered, so the total machinery energy input for orange production was 947 MJha$^{-1}$. Among all farmers, tractors were widely used in all operations. In many operations such as irrigation, tractors are only used to transport water pump motors and pipes so it was a cause of energy wastage and inefficiency. Generally, machinery power was primarily used in spraying operations. The low amount of machinery usage shows that in all operations human power was involved, mainly during the harvesting stage. Additionally, the large amount of diesel fuel used can be explained as the use of ancient tractors and inefficient motor pumps.

As can be seen in Table- 2, the total amount of energy input and output are 54284.8 and 59223.4 MJ ha$^{-1}$, respectively and the average orange yield was 31270.2 kg ha$^{-1}$.In similar research in the Mazandaran province of Iran, Namdari et al. (2011) found that the total energy used in various farm operations during orange production was 62375.1 MJ ha$^{-1}$. The highest energy input was provided by diesel fuel followed by chemical fertilizer. Additionally, Ozkan et al. (2004) found similar results for citrus productions in Turkey. Mohammadshirazi et al. (2012) found that the total energy requirement for the production of tangerine crops in the Mazandaran province of Iran is about 62260 MJ ha$^{-1}$ and chemical fertilizers had the highest energy consumption. Energy ratio, energy productivity and net energy gain are given in Table 3.

The Energy efficiency was calculated as 1.09. Energy productivity was calculated as 0.57 kg MJ$^{-1}$ meaning that for every 1 MJ of energy consumed farmers can produce 0.57 kg of orange fruit. Ozkan at al. (2004) in Turkey calculated the energy ratio as 1.25 for citrus production. In similar research Namdari et al. (2010) and Qasemi Kordkheili et al. (2013) reported that the energy ratio and the energy productivity of orchards for orange and nectarine production was 0.99, 0.52 kg MJ$^{-1}$ and 1.36, 0.77 kg MJ$^{-1}$ in the Mazandaran province of Iran, respectively. Also, net energy was measured as 4938.5 MJ ha$^{-1}$.

### ANN Energy Predictions

In this model input energies used for orange production included human power, machinery, diesel fuel, chemicals, electricity, fertilizer, farmyard manure and, water for irrigation. Orange yield was defined as the desired output parameter in the model. To find the best performance several networks were designed, trained and generalized. The results of tests corresponding to some network configurations show that best performance was achieved by MLP with 8-4-1 topology and momentum training algorithm. The result of statistical analyses is drawn in table 4.

From Table 4 it is clear that $R^2$, MAE and RMSE were calculated as 0.846, 0.324 and 0.383, respectively. Finally, this model was favored one as the best solution to estimate orange output on the basis of input. The test results of the best MLP network is shown in Figure 2.

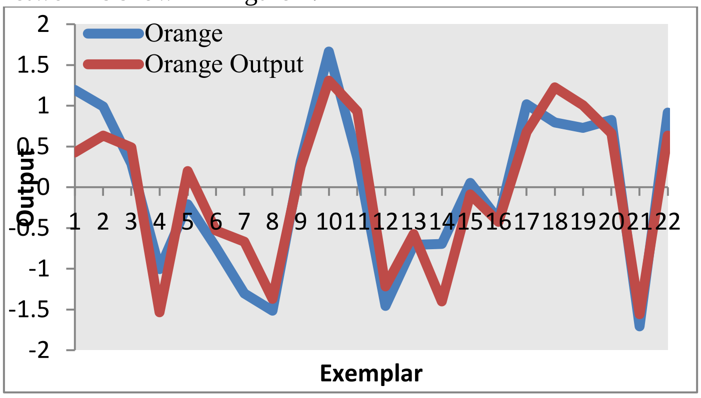


**Figure 2. Comparison of the Desired Output and Actual Network Output**

In this study momentum training algorithms were better than LM for most of the networks. This model has the ability of learning the relationship between 8 inputs and output parameter for studied orchards and predicts the output. Figure 3 illustrates the topology of a simple, fully connected three-layer MLP network with 8-4-1 architecture.

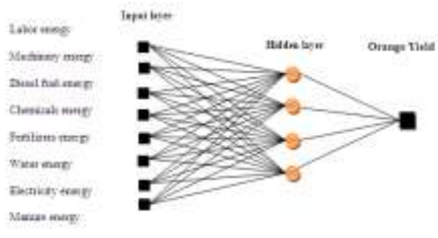


Figure 3. Structure of MLP network used in this research

Rahman and Bala (2010) reported that a model consisting of an input layer with six neurons, 2 hidden layers with nine and five neurons, and one neuron in the output layer was the best model for predicting jute production in Bangladesh. In other study on kiwifruit production in Mazandaran province of Iran, Mohammadi et al. (2010) developed an ANN model between input energies and the yield value of kiwifruit production and concluded that the ANN model with a 6-4-1 structure was the best model for predicting the kiwifruit yield in the surveyed region. Also in a study on canola production in Iran Mousavi-Avval et al. (2011) reported that the ANN model consisting of one input layer with eight input variables, two hidden layers with six and two neurons, respectively, and one output layer with one output variable, can predict the yield value with higher accuracy. Zangeneh et al. (2010) reported that the ANN model with 13-4-1 configuration was the best model to estimating machinery energy ratio (MER) indicator for potato production in

Iran. Pahlavan et al. (2012) used an ANN model for predicting greenhouse basil production in Iran. Their results showed that an ANN model with a 7-20-20-1 topology predict ted yield values with highest accuracy. In the optimal model, the values of the model's outputs correlated well with the actual outputs, with a coefficient of determination ($R^2$) of 0.976. For these configurations, RMSE and MAE values were 0.046 and 0.035, respectively.

**Sensitivity Analysis**

To estimate the predictive ability and validity of the developed model, sensitivity analysis was applied. Sensitivity analysis is especially useful in pinpointing which assumptions are appropriate variables for additional data collection to narrow the degree of uncertainty in the results (Mobtaker et al., 2010). Sensitivity analysis is normally done by changing one parameter at a time and observing what happens to other variables and provides an understanding of the individual variable's usefulness (Taki et al., 2012). The ability of the model was determined by comparing and examining the output produced within the validation stage with the calculated values. The momentum model was trained by withdrawing each input item one at a time while not changing any of the other items for every pattern. It is evident that fertilizer energy had the highest sensitivity on output (29.71%), followed by water for irrigation. Furthermore, the sensitivity of electricity was the lowest. The results are shown in Figure 4.

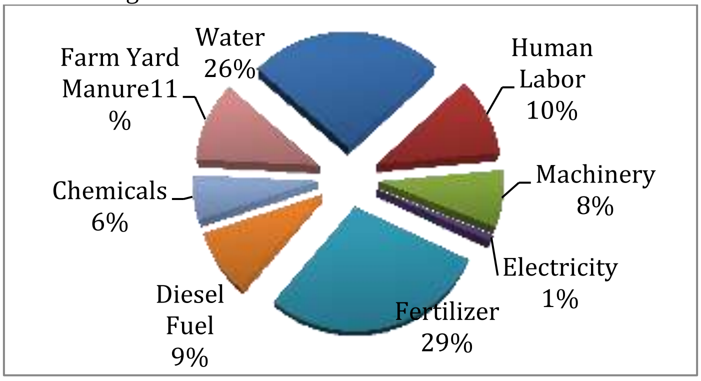


**Figure 4. Sensitivity analysis diagram**

Pahlavan et al. (2012) reported that chemical fertilizer energy had the highest sensitivity on output for basil production, followed by farm yard manure, diesel fuel and chemical inputs. It was also found that the sensitivity of electric, human and transportation energies was relatively low. Taki et al. (2012) in their survey on wheat production in Esfahan province of Iran, reported that human energy had the highest sensitivity on output (55%), followed by diesel fuel, while the sensitivity of irrigation was relatively low. Finally, the results of this study, is proposed to farmers to predict the crop yield with respect to the quantity of energy.

**Conclusion**

Totally ANNs are known as mathematical techniques designed to accomplish a variety of tasks. Developing an effective prediction model for orchards is of use to farmers in assisting them to adopt efficient production policies. In this study, the energy balance between the input and output for orange production in the Sari region of Iran was explored The total amount of energy consumed and total output energy for orange production were 56.7 GJ $ha^{-1}$ and 59.2 GJ $ha^{-1}$, respectively. Among input energy sources, diesel fuel and chemical fertilizers had the highest share, respectively. Energy ratio and energy productivity were calculated as 1.09 and 0.57 kg $MJ^{-1}$, respectively. Energy productivity and net energy were calculated as 1.09, 0.57 kg $MJ^{-1}$ and 4938.5 MJ $ha^{-1}$, respectively. Additionally, artificial neural networks (ANNs) model for prediction of orange yield based on the energy inputs was developed. The resulting tests showed that best performance was achieved by a momentum training algorithm resulting in $R^2$=0.846, and MAE= 0.324 and RMSE=0.383 with 8-4-1 topology. Also, sensitivity analysis revealed that fertilizer and electricity energy had the highest and the lowest sensitivity on output, respectively.

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**Table.1. Energy equivalent coefficients of inputs and output**

| Item | Units | Energy equivalent (MJ unit$^{-1}$) | References |
|---|---|---|---|
| Input<br>1.Diesel Fuel | l | 47.8 | (Rahbari et al., 2013) |
| 2.Electricity | kWh$^{-1}$ | 11.93 | (Mohammadi and Omid. 2010) |
| 3.Human Power | h | 1.96 | (Qasemi kordkheili et al., 2013) |
| 4.Water for irrigation | m$^3$ | 1.02 | (Qasemi kordkheili et al., 2013) |
| 5.Machinery | kg | 62.7 | (Singh and Mital 1992) |
| 6.Fertilizer | kg | | |
| Nitrogen | | 66.44 | (Mohammadi and Omid. 2010) |
| Phosphate ($P_2O_5$) | | 12.44 | (Mohammadi and Omid. 2010) |
| Potassium ($K_2O$) | | 11.15 | (Mohammadi and Omid. 2010) |
| Sulfur (S) | | 1.2 | (Mohammadi et al. 2010) |
| 7.Farmyard manure | kg | 0.3 | (Qasemi kordkheili et al., 2013) |
| 8.Chemicals | kg | | |
| Herbicides | | 238 | (Rafiee et al., 2010) |
| Pesticides | | 199 | (Namdari et al., 2011) |
| Fungicide | | 92 | (Ozkan et al., 2004) |
| Output | | | |
| Orange | kg | 1.9 | (Ozkan et al., 2004) |

**Table-2 Energy input sources, output and their energy equivalents for orange production.**

| Input | Quantity per unit area (Unit ha$^{-1}$) | Total energy equivalent (MJ ha$^{-1}$) |
|---|---|---|
| 1.Diesel Fuel (L) | 281.9 | 13475.3 |
| 2.Electricity (kWh) | 363.9 | 4352.5 |
| 3.Human Power (h) | 1342.3 | 2631.3 |
| 4.Water (m$^3$) | 11835.5 | 12072.3 |
| 5.Machinery (kg) | 4664.1 | 974.81 |
| 6.Fertilizers (kg) | | 12418.4 |
| Nitrogen | 91.5 | 6079.2 |
| Phosphate ($P_2O_5$) | 326.8 | 4065.3 |
| Potassium ($K_2O$) | 200.4 | 2234.4 |
| Sulphur (S) | 33.0 | 39.6 |
| 7.Farmyard manure | 15891.1 | 4768.8 |
| 8.Chemicals (kg) | | 3590.0 |
| Herbicides | 8.3 | 1990 |
| Pesticides | 3.99 | 795 |
| Fungicide | 8.75 | 805 |
| Total energy input | | 54284.8 |
| Total energy output | 31170.2 | 59223.4 |

**Table-3. Energy input-output in orange production.**

| Item | Unit | Value |
|---|---|---|
| Energy Efficiency | - | 1.09 |
| Energy Productivity | kg MJ$^{-1}$ | 0.57 |
| Net Energy | MJ ha$^{-1}$ | 4938.5 |

**Table 4 statistical analyses**

| Item | Orange |
|---|---|
| $R^2$ | 0.846 |
| MAE | 0.324 |
| RMSE | 0.383 |

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