

# THE USE OF ARTIFICIAL NEURAL NETWORKS IN ENERGY USE MODELING IN BROILER FARMS: A CASE STUDY OF MERSİN PROVINCE IN THE MEDITERRANEAN REGION

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**Abstract.** This study presents the application of Artificial Neural Network (ANN) techniques to estimate the total energy use of broiler farms. Chicken meat is shown as one of the important parameters in the modeling of energy use efficiency of broiler farms. However, the measurement of this extremely important parameter is difficult and takes a long time to obtain the desired results. In order to overcome such difficulties, scientists have tried to develop alternative methods. The farm-scale data used in the study was obtained from 30 broiler farms in Mersin (Turkey) province in 2018. In the application of ANN model, consumed feeds, electricity, fuel, water, broiler farms, chicks, human labor and machinery parameters used in the farm are used as input; broiler poultry meat and fertilizer parameter are used as output. In addition, the total energy equivalent estimates of chicken meat were made using various input combinations to investigate the best results model. The highest coefficient of determination ( $R^2$ ) (0.936) and the lowest root mean square error (RMSE) and the mean absolute error (MAE) values were found to be 0.232 and 0.019, respectively. The results showed that the ANN model is a very promising approach for the estimation of total energy equivalent of chicken meat in broiler farms.

**Keywords:** *artificial neural networks, energy efficiency, broiler chicken, sustainable, modeling*

## Introduction

The need to provide adequate food for the increasing population of the world has increased energy consumption in agriculture. Increased population and energy demands have forced governments to work on the efficiency of energy use. This issue makes agriculture vulnerable to oil prices (Taki and Yildizhan, 2018). Agriculture, as an efficient part of the economy, plays an important part in national production. With the reduction of energy resources, people will be forced to produce more food with less energy consumption in the future (Rohani et al., 2018). Agriculture is not only an energy consumer but also an important energy supplier (Almasi et al., 2008). Poultry meat offers significant potential to meet human nutritional needs (Folorunsho and Onibi, 2005). 35 g protein of animal origin is recommended for daily intake by FAO (FAO, 2011). In human nutrition, one third of the meat consumed in the world is obtained from broilers (Atilgan and Koknaroglu, 2006). Efficient use of energy in agriculture reduces environmental problems, prevents the destruction of natural resources and develops sustainable agriculture as an economic production system (Hatirli et al., 2005). In animal production systems, energy and feed are the main components of production costs (Rivera-Torres et al., 2010). Energy efficiency relates to the reduction of inputs purchased in agricultural production. The modeling capability

of ANN has made them the most popular tool for modeling the biological processes of complex systems with nonlinear properties (Kologirou, 1999). Artificial neural networks have a high approach and have a great advantage in a short time such as problem solving (Bechtler et al., 2001). ANN is applied in a wide area such as energy, mathematics, engineering, medicine, economy, environment and agriculture (Safa and Samarasinghe, 2001). ANN is one of the smartest techniques that are flexible and do not require too much physical complex operation (Yazdani et al., 2009). ANN is an optimization algorithm in which the learning process is tried to be modelled mathematically. ANN is a simple approach to a complex process, but uses the basic concepts inherent in the learning processes of people and animals. The ANN imitates the human brain's ability to learn by experimenting to produce solutions to problems that require a person's thinking and observing abilities. Learning in humans occurs by adjusting the synaptic connections between nerve cells (neurons). Since one birth, because of the process of learning by experience, the brain shows a continuous improvement. As the number of experience increases, synaptic connections are adjusted and new connections are created. In this way, learning takes place. This also applies to ANN. Learning is through training, using examples. By processing the input and output data, the training algorithm using this data, it is possible to re-adjust the connection weights until a convergence is achieved (Keskin and Taylan, 2007). ANNs are universal function estimators that work better than traditional function approach methods (Farjam et al., 2014). Classical regression analysis does not give any good results due to the nonlinear complex relations resulting from the nature of the problem. There are other methods that can be used more appropriately in cases of uncertainty. There are various methodologies in the literature, such as artificial neural networks (ANN), fuzzy logic, adaptive neuro-fuzzy systems which can be expressed as flexible methods. ANN models can be used to estimate the performance of the energy efficiency of broiler farms (Yurtoglu, 2005). In efficient energy use in agriculture, mathematical models have been used to find the relationships between the inputs and outputs of a production process (Pahlavan et al., 2012). Mathematical functions are of great importance in finding the relationship between inputs and yield by various methods (Hatirli et al., 2006). In study conducted in Iran using artificial neural networks; total equivalent input and output energy in broiler production was calculated as 153.79 and 27.45 GJ per 1000 birds, respectively (Amid and Gundoshmian, 2016). Rahman and Bala used artificial neural networks to estimate the dry matter of the cannabis plant in Bangladesh using parameters dependent on climatic conditions. They concluded that the best model had two hidden layers, the 6-9-5-1 structure (Rahman and Bala, 2010). Houshyar et al. in the wheat production in Iran, ANN was used. The best model for this study was the GFFN model with a hidden layer and the LM training algorithm with  $R^2 = 0.95$  and  $RMSE = 0.071$  (Houshyar et al., 2010). Using artificial neural network, Taki et al. have concluded that the optimal network for the estimated output energy of wheat production has two secret layers, each containing 8 neurons and which can be well predicted (Taki et al., 2012). In another study, Zangeneh et al. have compared the results of the implementation of two different approaches, namely, parametric model (PM) and ANN models, to evaluate the economic indices that benefit economic efficiency, total production costs and the cost ratio of the potato crop (Zangeneh et al., 2011). A study was carried out on the estimation of the energy demand of greenhouses by artificial neural network. In this study  $R^2$ , RMSE and MAE were found to be 0.93, 0.187 and 0.058, respectively (Trejo-Perea et al., 2009). Some other non-linear models such as

artificial neural networks, adaptive neuro-fuzzy inference system and nonlinear similar studies have been used in regression technique (Ekici and Aksoy, 2011; Mellit and Kalogirou, 2011; Talebizadeh and Moridnejad, 2011; Nefeslioglu et al., 2008; Yagiz et al., 2009; Dagdelenler et al., 2011). A multi-layered ANFIS has been used to estimate the yield of agricultural products (Naderloo et al., 2012; Khoshnevisan et al., 2014a, 2014b). In Iran, Heidari et al., in a study done in Yezd province measured energy efficiency of five-input and two-output parameters and broiler units, 16 were found to be fully efficient from 44 poultry farms (Heidari et al., 2011a). Heidari et al. using the Artificial Neural Network models estimated the Benefit Cost Ratio (BCR) of chicken farms in the tropical regions of Iran (Heidari et al., 2011b). The neural network used a multilayered feed network with five neurons (bird cost, labor cost, food cost, fuel cost and electricity cost) in the input layer and a neuron (benefit-cost ratio) in the output layer (Layer structure 5-20-1). Statistical indicators were estimated in  $R^2$ , RMSE, MAE and to verify the model. The indicators were calculated at 0.978, 0.002, 0.037 and 2.695 (Heidari et al., 2011b). Sefeedpari et al., in order to estimate the energy consumption of egg production farms in Iran, they used a three-entry ANN model to estimate variables such as fuel energy, electricity and feed energy (Sefeedpari et al., 2012). Atilgan and Koknaroglu according to the results of energy analysis used in broiler production units, showed that larger production units had higher energy efficiency compared to smaller production units (Atilgan and Koknaroglu, 2006). The electricity, fuel and manpower used in the 60,000-capacity broiler farm are reported in the winter 2395.8, 38563.88 and 94.85 MJ, respectively, and in the summer were 3359.5, 66.124, and 94.58 MJ, respectively (Sedaghat Hoseyni et al., 2008). Risse et al., who studied poultry farms as an energy source (Risse et al., 2007). reported that poultry manure saved 283 million gallons of fuel in the United States. In this study, Artificial Neural Network (ANN) models are applied for efficient use of Broiler Farms and estimation of total energy use.

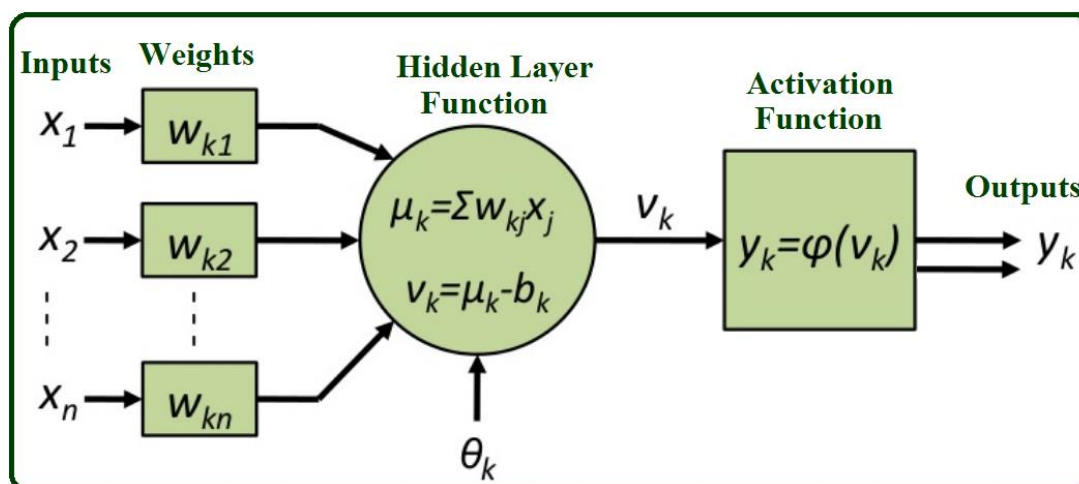
### ***Artificial neural networks (ANN)***

ANN is a sub-branch of artificial intelligence. The artificial working principle of the human brain is the artificial systems that have adopted the model. ANN is one of the most popular subjects of modern science with its ability to learn, adapt, ability to work with little information, fast work and identification. ANNs work with the principle of increasing knowledge and experience through learning and producing results by benefiting from the learning (Oztemel, 2003). Environment, agriculture, engineering, medicine, such as employees working in various areas of the sphere of their own areas of expertise, began to develop applications in their own fields. This interest is further strengthened by the theoretical and practical successes. It has been seen that some areas that seem to be unique to human intelligence can be expressed numerically, and thus machines can perform learning and recalling in a surprisingly similar way to human intelligence. Artificial neural networks are a powerful computational system inspired by the structure and learning characteristics of biological neuron cells and are very powerful classifiers in pattern recognition. Artificial neural networks, especially with the development of computer technology, have found a wide range of applications in the field of engineering (Kalogirou, 1999). Artificial neural networks are parallel information processing structures with the following characteristics:

- Inspired by a biological neuron, a mathematical model was introduced.
- It consists of a large number of processing elements connected to each other.
- Connection holds information with weights.

- A processing element can react dynamically to the input warnings and the response is entirely dependent on local information (the input signal through the connections and link weights that affect the respective processing element).
- It has learning, recalling and generalizing skills thanks to the connection weights set by the training data.

These outstanding features provide the ability to solve complex problems in artificial neural networks. It has found wide application areas in the fields of modeling and control. ANNs are first trained using the available data and then tested with unused data during training. Although training takes quite a long time; they decide very quickly during use. They found a wide range of applications in modeling both linear and nonlinear systems because of their ability to tolerate learning, generalization and errors and to take advantage of faulty samples (Haykin, 1994). ANN is looking at the examples of events and making generalizations about these events, collecting information and using the information they have learned when they have never seen them before and can decide on those examples (Ozcalik and Kucuktufekci, 2003). The concept of artificial neural networks (ANN) emerged with the idea of mimicking the working principles of the human brain on digital computers and the first studies focused on the mathematical modeling of neurons. Studies have shown that neurons exchange information with neighboring neurons. The so-called artificial neural networks are composed of neurons coming together in certain forms. ANN models differ from conventional models with non-algorithmic parallel and distributed information processing capabilities. Thanks to these different features, ANN can easily and quickly perform complex and non-linear accounts. Non-algorithmic and very intense parallel operations can be performed in parallel with the ability to learn and parallel distributed memory has led to new perspectives in the calculation. Input layer neurons transmit values to the next information processing layer elements through links that retrieve input information. This process continues until the output layer is reached. This type of information flow is known as the network feed forward network, which occurs in one direction. A typical ANN model is given in *Figure 1*. ANN models are configured as single or multiple inputs, and single or multiple outputs.



*Figure 1. Artificial neural network model*

### ***Feed forward back propagation artificial neural network (FFBPANN) model***

In this study, ANN (i, j, k) model is created to show input, hidden and output layers of icons i, j and k, respectively. Each layer is composed of many neurons and is bound by weight clusters between layers. The way of attachment and the number of neurons in each part may vary. Communication between neurons in the same section is not allowed. At the beginning of this training process, connection forces are assigned as random values. The learning algorithm changes the force until each iteration is completed with success. When the iteration process reaches a conclusion, the coupling forces obtain and store the available information in the samples used in the training process. When a new input group is presented, an output group is obtained by means of the learned and stored information in the connection forces of the artificial neural network with forward feed. Here, i and k values are 1 and j values are taken as 2, 3, 5, 7, 9, 10, 12 and ANN models are created. In this study, sigmoid function is used as transfer function, and back propagation algorithm based on generalized delta rule is used for ANN training (ASCE, 2000). The article aimed to use Artificial Neural Network (ANN) techniques to assess broiler farm energy consumption as a method that can sufficiently calculate the energy equivalent of chicken meat.

### **Materials and methods**

In this study, data were collected from 30 producers of broiler farms in Mersin. In the Mediterranean region city of Mersin, located south of Turkey. It is located between 36° 48' N and 34° 38' E (Fig. 2). The average annual temperature is approximately 19.2 °C and the total annual rainfall is 592.1 mm. Approximately 94% fall from October to May (GDM, 2017).



**Figure 2.** The location of the Mersin province involved in the presented study

Data on the production of broiler farms were collected with face-to-face surveys from the producer in 2018. Samples were selected using randomly selected random sampling method. Using the random sampling method of the producers who are producing in Broiler Farms in Mersin province where the production was made in 2018, the sample size was

calculated using the following equation (Newbold, 1994): The total number of registered farmers in Mersin in 2018 year was 35039 (GDAE, 2018). The Neyman method was applied to determine of number the farmer (Yamane, 1967).

$$n = \frac{N \times S^2}{(N-1)S_x^2 + S^2} \quad (\text{Eq.1})$$

where n is the required sample size, N population volume, S standard deviation,  $S_x$  sample is the standard deviation of the mean ( $S_x = d / z$ ), z is a reliability coefficient, d is based on the allowable error equation of the sample size (Eq. 1) In the Broiler Farms, the number of samples examined for production systems was 414. The permissible error (d) was defined as 5%, and for 95% reliability (z), the sampling size of 414 was calculated. First, the most common production systems for each Broiler Farm were identified, and then all inputs and outputs from the systems were identified and digitized, and then converted to energy units. With the addition of partial energies to the total energies per production unit, the energy inputs of each input were: chicks, human labor, fuel, electricity, feeds, water and machine. In order to estimate the energy in the MJ unit equivalents were used to find the input quantities as presented in *Table 1*.

**Table 1.** Energy equivalences for input and outputs

Particulars	Unit	Energy equivalent (MJ unit <sup>-1</sup> )	Reference
<b>A. Inputs</b>			
1. Chick	kg	10.33	Heidari et al., 2011b
2. Human labour	h	1.96	Karaagac et al., 2011; Mani et al., 2007
3. Diesel fuel	L	47.8	Kitani, 1999
4. Electricity	kWh	11.21	Pisghar et al., 2013
5. Feed	kg	12.98	Anonymous, 2014
6. Water	ton	0.63	Yaldız et al., 1993
7. Machinery (iron)	kg	27.73	Canakci and Akinci, 2006
8. Machinery (plastic)	kg	90	Canakci and Akinci, 2006
<b>B. Outputs</b>			
1. Chicken Meat	kg	10.33	Celik and Ozturkcan, 2003
2. Manure	kg	0.3	Singh, 2002

The data used in this study are the feed consumed in the broiler farms in 2018, the electricity consumed, the fuel consumed, the water consumed; human labor, machine parameters used in farms and chicken meat and fertilizer were obtained from 30 broiler farms in Mersin Province (*Table 1*). Energy equivalences for input and outputs are presented in *Table 2*. Energy input-output analysis in broiler chicken values are given. Poultry Equipment Used On Broiler Farms are given in *Figure 3*.

Statistical analyses of each of these data are given in *Table 3*. In this table, Xort,  $S_x$  and Cv represent the mean, standard deviation and variance, values of each data, respectively. The most variable data is water parameter (Cv = 0.564), feed parameter

has the highest correlation with chicken meat ( $R = 0.971$ ). Table 3 shows that the water parameter has the lowest correlation ( $R = -0.421$ ) with chicken meat.

**Table 2.** Energy input-output analysis in broiler chickens

Particulars	Unit	Quantity per unit area MJ (1000 birds)	Total energy equivalent (MJ/1000 bird)	Percentage of total energy (%)
<b>A. Inputs</b>				
1. Chick	kg	4000	41320	0.848
2. Human labour	h	1005.9	1971.564	0.040
3. Diesel fuel	L	940.8	44970.24	0.923
4. Electricity	kWh	12870.8	144281.668	2.962
5. Feed	kg	357012	4634015.76	95.148
6. Water	ton	41.622	26.22186	0.001
7. Machinery (iron)	kg	5.082	140.92386	0.003
8. Machinery (plastic)	kg	39.711	3573.99	0.073
Total inputs		375837.515	4870300.368	100
<b>B. Outputs</b>				
1. Chicken Meat	kg	245024	2531097.92	99.401
2. Manure	kg	47702.4	15264.768	0.599
Total outputs		292726.4	2546362.688	100
Energy ratio			0.52	

**Table 3.** Data used in the study and its statistical analysis

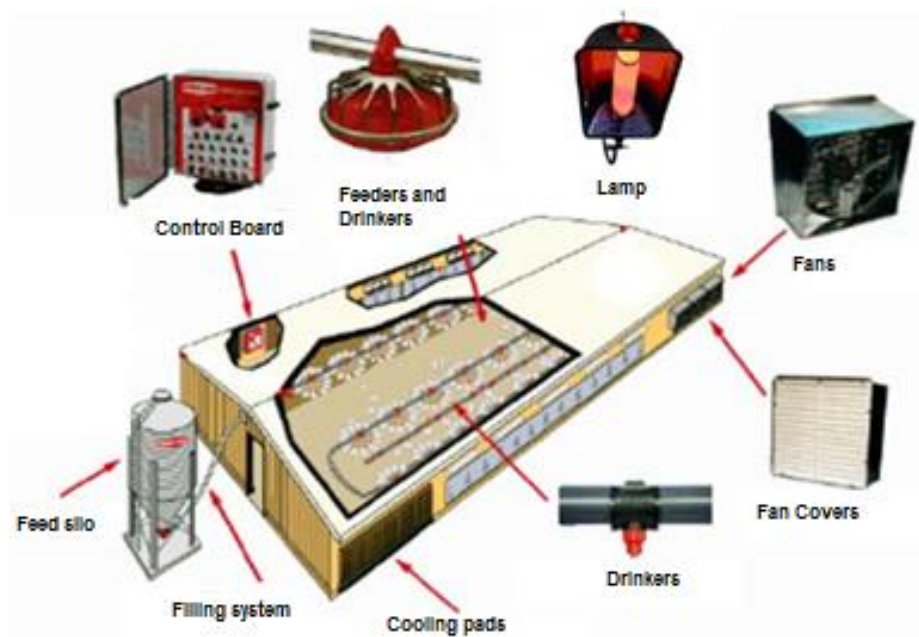
Data	$X_{ort}$	$S_x$	$C_v(S_x/X_{ort})$	Chicken meat and correlation (R)
Chicken meat (kg)	2531097.92	845263.8	0.334	1.000
Manure (kg)	15264.77	7311.824	0.479	0.638
Feed (kg)	4634015.76	1616092	0.349	0.971
Electricity (kWh)	144281.668	57424.1	0.398	0.816
Diesel fuel (L)	44970.24	18527.74	0.412	0.787
Chick (kg)	41320	19255.12	0.466	0.673
Machinery	3714.91	1824.023	0.491	0.619
Human labour	1971.56	1033.1	0.524	0.544
Water	26.22	14.78913	0.564	0.421

### **Implementation of feed forward back propagation artificial neural network model**

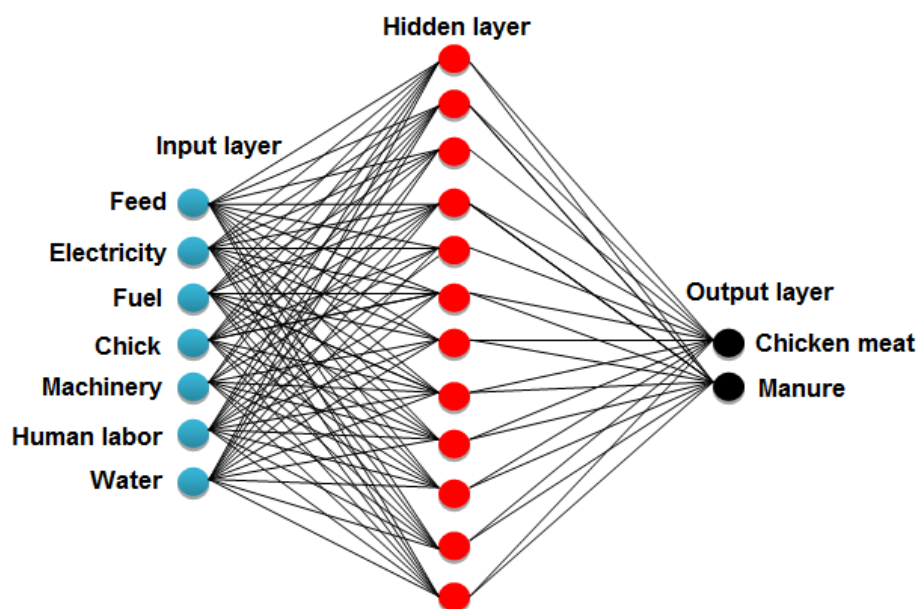
Analysis of 414 data from 30 broiler farms consisting of chicken meat and manure from seven input vectors (feeds, electricity, fuel, chicks, machinery, human labor and water) and two output vectors was considered. The data is divided into two groups to form the training and test sets. While constitute 276 data training sets, the remaining 138 data sets, were used as the test set in evaluating the performance of the program to the real values. The estimated network structure in Artificial Neural Networks model for broiler farms is given in Figure 4. In this study, for the evaluation of errors, the



coefficient of determination ( $R^2$ ), the square root of the mean square error (RMSE) and the mean absolute error (MAE) functions were used.



**Figure 3.** Poultry equipment used on broiler farms



**Figure 4.** Network structure estimated in the neural networks model for broiler farms

In this study, each model was tested with the test data set by training the training data set and the root of the square root mean square (RMSE) was calculated by using *Equation 2* (Landeras et al., 2008). One of the best evaluations used for statistical indices, the root of the mean square error (RMSE), as well as  $R^2$  estimation value were found with *Equation 3*. The related equations are:



$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i - y_i')^2}{N}} \quad (\text{Eq.2})$$

According to the  $R^2$  equation;  $m$  is the number of data tested, the estimated data on the  $O_i$  neural network,  $y_i$  is the amount of data calculated (Traore et al., 2010).

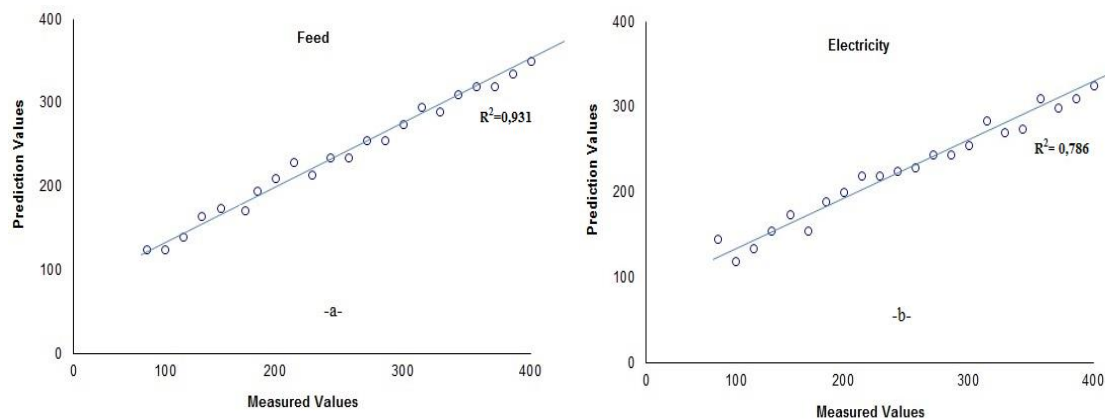
$$R^2 = \frac{\left[ \sum_{i=1}^m (y_i - \bar{y})(O_i - \bar{O}) \right]^2}{\sum_{i=1}^m (y_i - \bar{y})^2 \sum_{i=1}^m (O_i - \bar{O})^2} \quad (\text{Eq.3})$$

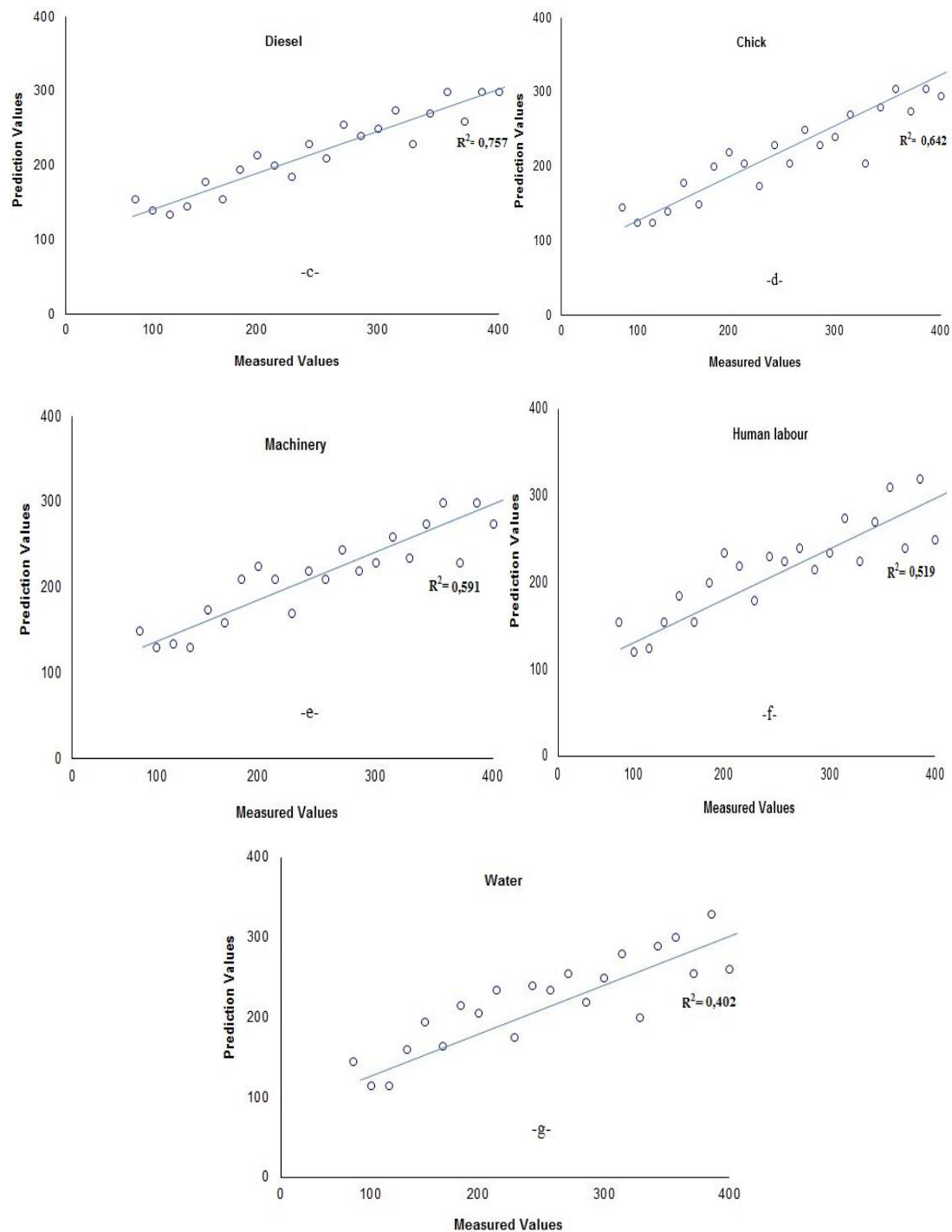
where  $\bar{y}$  is the average of the calculated data amount ( $y_i$ ) and the mean values of the estimated data amounts ( $O_i$ ) in the  $\bar{O}$  artificial neural network. In addition, mean absolute error (MAE) values were calculated (Eq. 4) (Trejo-Perea et al., 2009).

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - y_i'| \quad (\text{Eq.4})$$

#### ***Sensitivity analysis using feed forward back propagation artificial neural network model***

The choice of input parameters to be used in the FFBPANN model is important for the performance of the model (Khoshnevisan et al., 2014b). The effectiveness of the inputs in the model can be determined by sensitivity analysis. For the estimation of chicken meat, each input parameter was used individually and the most sensitive parameter was found with FFBPANN. The results are shown in Figure 5a-g. In addition, it was found that which combinations of inputs would give the most effective model by using sensitivity analysis (Table 4). As a result of sensitivity analysis, it was observed that all input parameters were important in estimating chicken meat. The feed input parameter is the most effective parameter for poultry meat prediction; Water as the least effective parameter is determined by the sensitivity analysis as shown in Figure 5a and g, respectively.





**Figure 5. a-g** Determination of performance of each input parameter in poultry meat estimation by FFBPANN

**Table 4.** Determination of the most effective FFBPANN model using sensitivity analysis

	MAE (%)	RMSE	Determination (R <sup>2</sup> )
Feed + Electricity + Fuel + Chick + Machinery + Human labour + Water	0.019	0.232	0.936

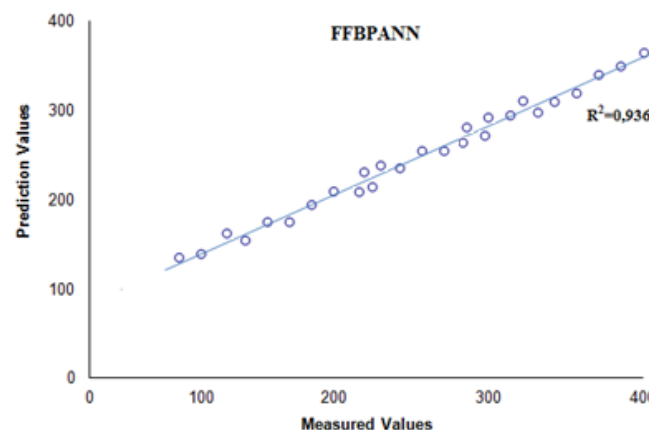
### ***Determination of the most appropriate FFBPANN model***

FFBPANN model, which gives the best result, was obtained after various trial errors. The determination of the FFBPANN model is shown in *Table 5*. RMSE and  $R^2$  performance functions are used to find the most effective FFBPANN model. In this study, the number of secret layer neurons is determined as 12 as seen in *Table 5* after various experiments. The highest performance is the ANN (7.12.2) model. It is also understood from *Table 5* that the maximum number of iterations is 1000 for the training of the model.

***Table 5. Determination of the most effective IBGYSA model***

ANN (number of neurons in layers)	Number of iterations	Determination factor ( $R^2$ )	Root of the mean square error (RMSE)
ANN(7,2,2)	1000	0.885	0.197
ANN(7,3,2)	1000	0.889	0.201
ANN(7,5,2)	1000	0.892	0.207
ANN(7,7,2)	1000	0.896	0.209
ANN(7,9,2)	1000	0.852	0.152
ANN(7,10,2)	1000	0.911	0.217
ANN(7,12,2)	1000	0.936	0.232
ANN(7,2,2)	2000	0.861	0.159
ANN(7,3,2)	2000	0.865	0.167
ANN(7,5,2)	2000	0.868	0.171
ANN(7,7,2)	2000	0.872	0.175
ANN(7,9,2)	2000	<u>0.843</u>	0.149
ANN(7,10,2)	2000	0.877	0.178
ANN(7,12,2)	2000	0.882	0.186

The model was tested after the training of the FFBPANN model. When the test set chicken meat predictions were compared with the measured chicken meat, it was observed that the estimates of FFBPANN were very close to the observed ones. *Figure 6* shows that the predicted values are very close to the observed values and their tendency is almost equal.



***Figure 6. FFBPANN model chicken meat predictions compared with measured chicken meat***

## Results

In this study, the data obtained from 30 broiler farms in Mersin province by using feed forward, back diffusion artificial neural networks FFBPANN model the energy consumption of poultry was tried to be estimated. In the network structures where the best results for the test and training data are obtained;  $R^2$ , MAE and RMSE etc. statistical analyses were performed. Training and test  $R^2$  values showed that the ANN used in this study gave high accuracy results. Each input parameter was used as an input in a separate model and the efficiency levels of each parameter in the estimation of chicken meat were found. As a result of this, the most effective parameter is that feed supply energy. Then the energy of electricity, fuel, chicks, machine and human labor are effective, respectively; water supply energy has been determined as the least effective parameter. Furthermore, sensitivity analysis was performed for the determination of the most effective model due to the fact that an effective Forward Feed Back Artificial Neural Networks FFBPANN model was dependent on the input parameters. As a result of sensitivity analysis, it has been observed that all input supply energy parameters have an influence on the model of Feed, Electricity, Fuel, Chicks, Machines, Human labor and Water, ANN model. As a result, for the broiler farm process, the Advanced Feed Back Flow Artificial Neural Networks model proved that using ANN in the estimation of chicken meat supply energy is a better technique than traditional mathematical modeling. It can be said that Broiler Farms can be used as a very effective model in the evaluation of energy use estimation due to the fact that they provide realistic and reliable estimates thanks to well-trained ANN parameters. The model developed in this study has an acceptable generalization ability. Since it is an effective analysis and identification method to simulate the nonlinear behavior of the Broiler Farms of ANN, it is concluded that it is used as a good performance evaluation method. The highest coefficient of determination ( $R^2$ ) 0.936 and the lowest root of the mean square error (RMSE) and the mean absolute error (MAE) values were found as 0.232 and 0.019, respectively. Sensitivity analysis showed that all input parameters (Chicken Meat) were important in estimating chicken meat. (Feed) Feed input parameter (Chicken Meat) is the most effective parameter for estimating chicken meat, Water was determined as the least effective parameter by sensitivity analysis.

Based on the findings of this study, ANN topologies are recommended. In the study conducted in the province of Mersin it has been found efficient in the estimation of energy usage of seven inputs, two output parameters and broiler farms by using ANN techniques.

## REFERENCES

- [1] Almasi, M., Kiani, S., Lavimi, N. (2008): Agricultural Mechanization. 4th Ed. – Jangal, Tehran.
- [2] Amid, S., Gundoshmian, M. T. (2016): Modelling energy efficiency in broiler production using multi layer perception artificial neural network approach (case study: Ardabil Province). – Animal Production Research 5(2): 73-85.
- [3] Anonymous (2014): CP. Istanbul: layer chicken feed characteristics. – <http://www.cpturkiye.com/tr/urunler/yem/kanatli-hayvan-yemleri/yumurta-tavugu-yemleri/>.

- [4] ASCE (2000): Task Committee on Application of Artificial Neural Networks in Hydrology (2000): artificial neural networks in hydrology. I: Preliminary concepts. – J. Hydrologic Engrg. ASCE 5(2): 115-123.
- [5] Atilgan, A., Koknaroglu, H. (2006): Cultural energy analysis on broilers reared in different capacity poultry houses. – Italian Journal of Animal Science 5: 393-400.
- [6] Bechtler, H., Browne, M. W., Bansal, P. K., Kecman, V. (2001): New approach to dynamic modeling of vapour compression liquid chillers: artificial neural networks. – Applied Thermal Engineering 21: 941-953.
- [7] Canakci, M., Akinci, I. (2006): Energy use pattern analyses of greenhouse vegetable production. – Energy 31: 1243-56.
- [8] Celik, L., Ozturkcan, O. (2003): Effects of dietary supplemental L-carnitine and ascorbic acid on performance, carcass composition and plasma L-carnitine concentration of broiler chicks reared under different temperature. – Archives of Animal Nutrition 57: 27-38.
- [9] Dagdelenler, G., Sezer, E. A., Gokceoglu, C. (2011): Some non-linear models to predict the weathering degrees of a granitic rock from physical and mechanical parameters. – Expert Syst. Appl. 38: 7476-7485.
- [10] Ekici, B. B., Aksoy, U. T. (2011): Prediction of building energy needs in early stage of design by using ANFIS. – Expert Syst. Appl. 38: 5352-5358.
- [11] FAO (2011): Food and Agriculture Organization. – <http://www.fao.org/3/i3396e/i3396e.pdf>
- [12] Farjam, A., Omid, M., Akaram, A., Fazel-Niari, Z. (2014): A neural network based modeling and sensitivity analysis of energy inputs for predicting seed and grain corn yields. – Journal of Agricultural Science and Technology 16: 767-778.
- [13] Folorunsho, O. R., Onibi, G. E. (2005): Assessment of the Nutritional Quality of Eviscerated Waste from Selected Chicken Types. – In: Onibi, G. E., Agele, S. O., Adekunle, V. A. J. (eds.) Proceedings of the 1st Annual Conference on Developments in Agriculture and Biological Sciences, 27th April 2005, Akure, Nigeria.
- [14] GDAE (2018): Republic of Turkey General Directorate of Agricultural Enterprises. <https://www.tarimorman.gov.tr/sgb/Belgeler/SagMenuVeriler/HAYGEM.pdf>–
- [15] GDM (2017): Republic of Turkey Ministry of Agriculture, Forestry General Directorate of Meteorology. – <https://www.mgm.gov.tr/?il=Mersin>.
- [16] Hatirli, S. A., Ozkan, B., Fert, C. (2005): An econometric analysis of energy input-output in Turkish agriculture. – Renewable and Sustainable Energy Reviews 9: 608-23.
- [17] Hatirli, S. A., Ozkan, B., Fert, C. (2006): Energy inputs and crop yield relationship in greenhouse tomato production. – Renew. Energy 31: 427-438.
- [18] Haykin, S. (1994): Neural Networks. A Comprehensive Foundation. – Prentice Hall, Upper Saddle River, NJ.
- [19] Heidari, M. D., Omid, M., Akram, A. (2011a): Optimization of energy consumption of broiler production farms using Data Envelopment Analysis Approach. – Modern Applied Science 5(3): 69-78.
- [20] Heidari, M. D., Omid, M., Akram, A. (2011b): Application of artificial neural network for modeling benefit to cost ratio of broiler farms in tropical regions of Iran. – Research Journal of Applied Science, Engineering and Technology 3(6): 546-52.
- [21] Houshyar, E., Sheikh-Davoodi, M., Bahrani, H., Kiani, S., Houshyar, M. (2010): Energy use forecasting for wheat production utilizing artificial neural network. – World Applied Science Journal 10: 958-962.
- [22] Karaagac, M. A., Aykanat, S., Cakir, B., Eren, O., Turgut, M. M., Barut, Z. B., Ozturk, H. H. (2011): Energy balance of wheat and maize crops production in Haciali undertaking. – 11th International Congress on Mechanization and Energy in Agriculture Congress, Istanbul, Turkey, pp. 388-391.
- [23] Keskin, M. E., Taylan, E. D. (2007): Stochastic modeling of flows in the middle Black Sea basin. – CCE - Chamber of Civil Engineers Technical Magazine 2007: 4271-4291.

- [24] Khoshnevisan, B., Rafiee, S., Mousazadeh, H. (2014a): Application of multi-layer adaptive neuro-fuzzy inference system for estimation of greenhouse strawberry yield. – *Measurement* 47: 903-910.
- [25] Khoshnevisan, B., Rafiee, S., Omid, M., Mousazadeh, H. (2014b): Prediction of potato yield based on energy inputs using multi-layer adaptive neuro-fuzzy inference system. – *Measurement* 47: 521-530.
- [26] Kitani, O. (1999): *Energy and Biomass Engineering*. CIGR Handbook of Agricultural Engineering. Vol. 5. – ASAE, St. Joseph, MI.
- [27] Kologirou, S. (1999): Applications of artificial neural networks in energy systems: a review. – *Energy Conversion and Management* 40(3): 1073-1087.
- [28] Landeras, G., Ortiz-Barredo, A., Lopez, J. J. (2008): Comparison of artificial neural network models and empirical and semi-empirical equations for daily reference evapotranspiration estimation in the Basque Country (Northern Spain). – *Agricultural Water Management* 95: 553-565.
- [29] Mani, I., Kumar, P., Panwar, J. S., Kant, K. (2007): Variation in energy consumption in production of wheat- maize with varying altitudes in hill regions of Himachal Pradesh, India. – *Energy* 32: 2336-39.
- [30] Mellit, A., Kalogirou, S. A. (2011): ANFIS-based modelling for photovoltaic power supply system: a case study. – *Renew. Energy* 36(1): 250-258.
- [31] Naderloo, L., Alimardani, R., Omid, M., Sarmadian, F., Javadikia, P., Torabi, M., Alimardani, F. (2012): Application of ANFIS to predict crop yield based on different energy inputs. – *Measurement* 45(6): 1406-1413.
- [32] Nefeslioglu, H. A., Gokceoglu, C., Sonmez, H. (2008): An assessment on the use of logistic regression and artificial neural networks with different sampling strategies for the preparation of landslide susceptibility maps. – *Eng. Geol.* 97: 171-191.
- [33] Newbold, P. (1994): *Statistics for Business and Economics*. – Prentice-Hall, Inc. Upper Saddle River, NJ.
- [34] Ozcalik, H. R., Kucuktufekci, A. (2003): Linear and inverse modeling of dynamic systems with artificial neural networks. – *KSU Journal of Science and Engineering* 6(1): 26-35.
- [35] Oztemel, E. (2003): *Artificial Neural Networks*. 3rd Ed. – Papatya Publications, Istanbul.
- [36] Pahlavan, R., Omid, M., Rafiee, S., Mousavi-Avval, H. (2012): Optimization of energy consumption for rose production in Iran. – *Energy for Sustainable Development* 16: 236-241.
- [37] Pisghar-Komleh, S. H., Omid, M., Heidari, M. D. (2013): On the study of energy use and GHG (greenhouse gas) emissions in greenhouse cucumber production in Yazd province. – *Energy* 59: 63-71. DOI: 10.1016/j.energy.2013.07.037.
- [38] Rahman, M. M., Bala, B. K. (2010): Modelling of jute production using artificial neural networks. – *Biosystems Engineering* 105: 350-356.
- [39] Risse, M., Das, K. C., Worley, J., Thompson, S. (2007): *Poultry Litter as an Energy Source*. – Department of Biological and Agricultural Engineering, University of Georgia, Athens, USA.
- [40] Rivera-Torres, V., Noblet, J., Dubois, S., van Milgen, J. (2010): Energy partitioning in male growing turkeys. – *Poult. Sci.* 89(3): 530-538.
- [41] Rohani, A., Taki, M., Abdollahpour, M. (2018): A novel soft computing model (Gaussian process regression with K-fold cross validation) for daily and monthly solar radiation forecasting (Part: I). – *Renewable Energy* 115: 411-422.
- [42] Safa, M., Samarasinghe, S. (2001): Determination and modelling of energy consumption in wheat production using neural networks: a case study in Canterbury Province, New Zealand. – *Energy* 36: 5140-5147.
- [43] Sedaghat Hoseyni, S. N., Almasi, M., Minaei, S., Barghaei, A. (2008): *Energy Recovery Systems of Industrial Complex for Production of Eggs*. – Ferdosi University, Mashhad.

- [44] Sefeedpari, P., Rafiee, S., Akram, A. (2012): Modeling of energy output in poultry for egg production farms using artificial neural networks. – *Journal of Animal Production Advances* 2(5): 247-253.
- [45] Singh, J. M. (2002): On farm energy use pattern in different cropping systems in Haryana, India. – Master of Science Thesis. International Institute of Management University of Flensburg, Sustainable Energy Systems and Management.
- [46] Taki, M., Yildizhan, H. (2018): Evaluation the sustainable energy applications for fruit and vegetable productions processes. Case study: greenhouse cucumber production. – *Journal of Cleaner Production* 199: 164-172.
- [47] Taki, M., Ajabshirchi, Y., Mahmoudi, A. (2012): Prediction of output energy for wheat production using artificial neural networks in Esfahan province of Iran. – *Journal of Agricultural Technology* 8(4): 1229-1242.
- [48] Talebizadeh, M., Moridnejad, A. (2011): Uncertainty analysis for the forecast of lake level fluctuations using ensembles of ANN and ANFIS models. – *Expert Syst. Appl.* 38: 4126-4135.
- [49] Traore, S., Wang, Y. M., Kerh, T. (2010): Artificial neural network for modeling reference evapotranspiration complex process in Sudano-Sahelian zone. – *Agricultural Water Management* 97: 707-714.
- [50] Trejo-Perea, M., Herrera-Ruiz, G., Rios-Moreno, J., Castaneda, R., Miranda-Raiza, E. (2009): Greenhouse energy consumption prediction using neural networks models. – *International Journal of Agricultural & Biology* 11(1): 1-6.
- [51] Yagiz, S., Gokceoglu, C., Sezer, E., Iplikci, S. (2009): Application of two nonlinear prediction tools to the estimation of tunnel boring machine performance. – *Eng. Appl. Artif. Intell.* 22: 818-824.
- [52] Yaldiz, O., Ozturk, H. H., Zeren, Y., Bascetincelik, A. (1993): Energy usage in production of field crops in Turkey. – 5th International Congress on Mechanization and Energy in Agriculture, Kusadasi, Turkey, pp. 527-536.
- [53] Yamane, T. (1967): *Elementary Sampling Theory*. – Prentice Hall, Englewood Cliffs, NJ.
- [54] Yazdani, M., Saghafian, B., Mahdian, M., Soltani, S. (2009): Monthly runoff estimation using artificial neural networks. – *Journal of Agricultural Science and Technology* 11: 335-362.
- [55] Yurtoglu, H. (2005): *Artificial neural network modeling and forecasting methodology: the case of Turkey for some macroeconomic variables*. – Thesis. General Directorate of Economic Models and Strategic Research, Ankara.
- [56] Zangeneh, M., Omid, M., Akram, A. (2011): A comparative study between parametric and artificial neural networks approaches for economical assessment of potato production in Iran. – *Spanish Journal of Agricultural Research* 3: 661-671.