JLSB
Journal of
Life Science and Biomedicine

J. Life Sci. Biomed. 4(4):305-311, 2014

ISSN 2251-9939

Evaluation the Ability of Different Artificial Intelligence-Based Modeling Techniques in Prediction of Yield Using Energy Inputs Data of Farms

Sajjad Firoozi, Mohammad Javad Sheikhdavoodi and Móslem Sami*
Department of Agricultural Mechanization, Faculty of Agriculture, Shahid Chamran University of Ahvaz, Iran.

*Corresponding author's e-mail: sami.moslem@gmail.com

ORIGINAL ARTICLE
Received 10Jan. 2014
Accepted 10Mar. 2014

ABSTRACT: Modelling of farm output yield on the basis of input energies will help to improve the energy efficiently of agricultural practice. In this study the ability of various types of artificial neural networks and Neuro-fuzzy inference models were evaluated and the sensitivity of greenhouse cucumber yield to different energy inputs was evaluated using the best developed models. The results showed that a Multi-Layer Perceptron model with six inputs and four neurons in each of four hidden layers provided the best results with determination coefficient of 0.94 and the mean square error of 0.0040. The results of artificial neural networks were comparatively better than those of Neuro-fuzzy inference model. The sensitivity analysis results showed that the cucumber production is more sensitive to labour energy than other energy inputs.
Keywords: Energy, ANN, CANFIS, Prediction Model, Yield Sensitivity

INTRODUCTION

Energy use in agriculture has increased in response to increasing populations, limited supply of arable land and desire for an increasing standard of living. In all societies, these factors have encouraged an increase in energy inputs to maximize yields, minimize labour-intensive practices or both [1]. Analysis of energy consumption has a great importance for two reasons. Firstly, in order to make better economic decisions about proper and essential energy, policy makers and decision makers should know the way how the amounts of energy of consumption are formed in different economical parts like the agricultural section. Therefore, every research carried out in a scientific framework to explain this subject is of importance. Secondly, in order to have planning in national level or even in an economical level, state economic authorities [including governmental and private] need to, predict factors affecting the price of merchandise and products of different sections in different time intervals , through an appropriate modeling [2]. In recent years a great attention has been given to the energy analysis of agricultural activities as one of the biggest sectors of energy consumer and also producer. Different studies have also tried to evaluate the energy efficiency of various agricultural productions such as cereals [3, 4], oilseeds [5, 6], greenhouse crops [7, 8], hay crops [9, 10] fruits [1, 11] vegetables [12, 13] etc. In the energy area, a wide range of models has been used to modeling future energy demand [14]. To increase the efficiently of energy use and production of agricultural farms in the resent years many models using different approaches have been presented such as regression based [4, 15, 16], neuronal networks [17- 19], neuro-fuzzy inference models [20,21] etc. These models predict the outputs of farms according to energy input parameters and also model the energy consumption pattern of production processes to help to increase the farm yield by minimum increase in the energy inputs. However there are some studies that tried to compare the ability of different artificial and mathematical prediction models in different areas [22- 25], based on the literature, its seems there is no study on the efficiency comparison of artificial intelligence methods for prediction of farm outputs according to energy inputs. In this study we tested and compared the two main approaches of Artificial Neural Networks (ANN) and Adaptive coactive Neuro-Fuzzy Inference System (CANFIS) for development of prediction models and finally evaluated the sensitivity of cucumber production to the energy inputs.

MATERIAL AND METHODS

Study area and data collection southwest: Data used in this study were obtained from 60 farmers growing single crop of cucumber in a greenhouse in the Lorestan and Markazi provinces of Iran by using a face-to-face questionnaire method performed in season 2011-2012. The selection of greenhouses was based on random sampling method. Markazi and Lorestan provinces are located in the southwest of Iran, within 32° 37' and 35° 35' north latitude and 46° 51' and 51° east longitude. The simple random sampling method was used to determine the survey volume, as described by Ghasemi Mobtaker et al. [9]:

$$n = \frac{N(s\times t)^2}{(N-1)d^2+(s\times t)^2} \qquad (1)$$

To cite this paper: Firoozi, S., Sheikhdavoodi, MJ. And Sami, M. 2014. Evaluation the Ability of Different Artificial Intelligence-Based Modeling Techniques in Prediction of Yield Using Energy Inputs Data of Farms. *J. Life Sci. Biomed.* 4(4):305-311.
Journal homepage: http://jlsb.science-line.com/

Where n is required sample size, N is the number of holdings in target population, s is standard deviation, d is acceptable error (permissible error was chosen as 5%) and t is confidence limit (1.96 in the case of 95% reliability).

Artificial neural networks: The ANN is a form of artificial intelligence that its structure is based on the human brain's biological neural processes [26]. A neural network consists of simple synchronous processing elements, called neurons, which are inspired by biological nerve system [27]. The mathematical model of a neural network comprises a set of simple functions linked together by weights. The most common ANNs used, consist of an input layer, an output layer and a number of hidden layers which link the inputs to outputs. In complex problems more than one layer is necessary that the number of the hidden neurons depends on the nature of the investigated problem. These neural networks are called multilayer neural networks. The output of neurons may be feed back to the same or previous layers. There are various methods to determine the number of the hidden neurons [28, 29]. Each layer includes a number of elements called neurons or nodes. Hidden neurons with appropriate nonlinear transfer functions are used to process the information received by the input neurons. The transfer functions may be a linear or a non-linear function. There are several transfer functions, such as Logistic, Hyperbolic tangent, Gaussian, and Sine. The output depends on the particular transfer function used [30]. 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 [19].

In this study, two different types of ANNs were developed for predicting output. The first ANN model was Multi-Layer Perceptron (MLP) which is the most commonly used neural network structure in ecological modeling [31]. In this network, the data flows forward to the output continuously without on any feedback. The second tested ANN model was Radial Basis Function (RBF). RBF networks are nonlinear hybrid networks typically containing a single hidden layer of processing elements. This layer uses Gaussian transfer functions, rather than the standard sigmoid functions employed by MLP [31].

Neuro-fuzzy inference model: Presented by Jang et al. [32], CANFIS is one of the common types of neuro-fuzzy algorithms. CANFIS uses ANN learning algorithms to adapt the fuzzy inference model parameters that best allow the associated fuzzy inference system to track the given input/output data. Model parameters are adjusted using either a back-propagation algorithm alone, or in combination with a least squares type of method. This learning method works similarly to that of neural networks. CANFIS uses the advantages of both methods which able it to model very complex situation with the minimum information. The fundamental component for CANFIS is a fuzzy neuron that applies membership functions to the inputs. Basically, two membership function types can be used: general bell and Gaussian. The general architecture of CANFIS consists of five layers that are shown in Figure 1. In layer 1, the fuzzification of the input is performed by each node. Each node in this layer is the membership grade of a fuzzy set (A1, A2, B1 or B2) and specifies the degree to which the given input belongs to one of the fuzzy sets. Layer 2 receives input in the form of the product of all output pairs from the first layer. Two components are present in the next third layer in the network. The third layer has two components. The upper component of this layer applies the membership functions to each of the inputs, while the lower components is a representation of the modular network that computes, for each output, the sum of all the firing strength. The fourth layer of the network performs the weighted normalization of the outputs of the two components of the third layer. The final output of the network is the product of layer 5. Two fuzzy models are mainly used: the Tsukamoto model and the Sugeno (TSK) model [33].

Performance evaluation criteria: Two different types of criteria were selected to evaluate the performance of the models including; mean square error (MSE) and determination coefficient (R^2). The two performance evaluation criteria used in the current study can be calculated using Eq. 2 and 3 [30].

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2}\right) \qquad (2)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_i - z_i)^2 \qquad (3)$$

Where 'n' is the number of the points in the data set, and 't' and 'z' are actual output and predicted output sets, respectively.

Energy Calculation: Input and output energy are expressed in the term of MJ/ha and are calculated based on a mixed of data collected from the farms and energy equivalents. Every farm input in the form of energy is calculated by multiplying the amount of each input per hectare by its coefficient of energy equivalent. The energy equivalents for different inputs and outputs used in energy budget calculation are shown in Table 1 [35].

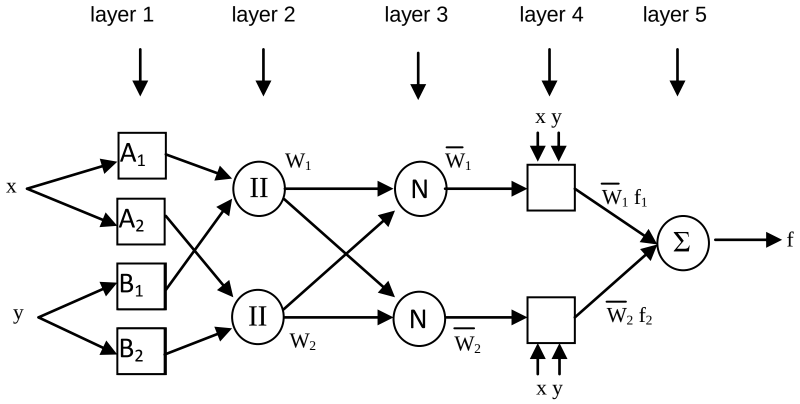

Figure 1. Architecture of the CANFIS model [34].

RESULTS AND DISCUSSIONS

Performances of MLP models: The energy inputs of labor, machinery, fuel, fertiliser, pesticide and electricity were selected as inputs of models and farm yield was selected as models output. Date were randomly grouped into three sets; training set (63%), cross validation set (16%) and testing set (20%). So, 38 samples out of 60 samples were considered for training, 10 samples were used for cross validation, and the remaining 12 samples were selected for testing. The ability of generalization of a network is evaluated by the validation data, the same time as it is trained. The data validation prevents over-learning of the model. Then a network is tested by data that did not participate in the training and validation phase, to present a related output. In this study NeroSolutions 5.07 software package [36] was used to develop different models.

To find the best topology we developed several ANN type networks and changed the number of hidden layers and neurons in each layer. The validity of the models was checked by comparing its output values with real outputs using calculated criteria. Calculated performance criteria of different models developed using various numbers of layers and neurons are given in Table 2. Among developed models, the best model consisted of an input layer with six input variables, four hidden layer with four neurons in it and one output (6-4-4-4-4-1- MLP). This topology had the least MSE and the highest R^2 for the output yield. However performance criteria of this model were very similar to the model consisted of two hidden layer with eight neurons in it (6-8-8-1- MLP). It is considerable that all models showed very good performance criteria. In all models no transfer function for the first layer was used but for the hidden layers and the output layer the hyperbolic tangent was used in each hidden layer.

Table 1. The energy coefficient of farms inputs

Inputs and output (unit)	Energy equivalent (MJ/unit)	References
1. Human Labor (h)	1.9	[41]
2. Machinery (kg)	62.7	[42]
3. Fuel		
(a) Diesel fuel (l)	47.8	[43]
(b) Natural gas(m^3)	49.5	[43]
4. Chemical Fertilizers (kg)		
(a) Nitrogen (N)	78.1	[41]
(b) Phosphate (P_2O5)	17.4	[41]
(c) Potassium (K_2O)	13.7	[41]
(d) Micro fertilizers	8.8	[20]
5. Manure (ton)	303.1	[41]
6. Pesticides (kg or l)		
(a) Insecticide	199.0	[34]
(b) Fungicide	92.0	[34]
(c) Herbicide	238.0	[34]
7. Electricity (kWh)	11.9	[41]

From Table 2 it is also considerable that the best topography was dependent on the value of layers*neurons. The low number of layers with low number of neurons provided the weakest models. By increasing the value of layers*neurons the model reliability increased. The high layers*neurons value decreased the model reliability again. In the past studies on the development of ANN models for energy analysis of agricultural farms, different number of layers and neurons were reported as best topologies. Rahman and Bala [36] 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 topology for predicting jute production in Bangladesh. Pahlavan et al. [30] predicted the basil yield with high accuracy using a (7-20-20-1) MLP topology. Zangeneh et al. [18] reported that the ANN model with 13-4-1 configuration was the best model for estimating machinery energy ratio indicator for potato production in Iran. Taki and Haddad [7] showed that (7-10-1-1)-MLP topography is the best ANN model for tomato yield prediction.

We also tried the RBF structure for development of ANN model with two topography of (6-4-4-4-1) and (6-8-8-1) that were the best combination of layers and neurons in MLP model (Table 2). The performance criteria of this models sowed that the performance of RBF type model is not as good as those of MPL models. The better performance of MLP models compared to RBF model was also reported by Rasouli et al. [37].

Table 2. The measured criteria of different ANN models

Model characteristics	**Measured criteria**			
Type	Layers number	Neurons number in each layer	MSE	R^2
MLP	1	2	0.0056	0.88
MLP	1	4	0.0055	0.76
MLP	1	8	0.0055	0.77
MLP	1	16	0.0091	0.83
MLP	2	2	0.0050	0.96
MLP	2	4	0.0060	0.88
MLP	**2**	**8**	**0.0040**	**0.90**
MLP	2	16	0.0096	0.83
MLP	3	2	0.0080	0.83
MLP	3	4	0.0050	0.90
MLP	3	8	0.0075	0.92
MLP	3	16	0.0058	0.88
MLP	4	2	0.0051	0.90
MLP	**4**	**4**	**0.0040**	**0.94**
MLP	4	8	0.0091	0.88
MLP	4	16	0.0098	0.84
MLP	5	2	0.0070	0.88
MLP	5	4	0.0050	0.90
MLP	5	8	0.0120	0.94
MLP	5	16	0.0121	0.93
RBF	2	8	0.0051	0.81
RBF	4	4	0.0090	0.65

Performances of CANFIS models: Various combinations of membership functions number and membership functions types were examined to find the best CANFIS model with minimum error. In the CANFIS system, each input parameter might be clustered into several class values in layer 1 to build up fuzzy rules and each fuzzy rule would be constructed using two or more membership functions in layer 2. In this study the different model using two and three membership functions were developed. Also we test two different type of membership functions shape including bell and Gaussian curves.

Table 3 shows the mean square errors and coefficient of determination values for the testing phases of different CANFIS model developed. This table shows that the model developed using three bell-shaped membership functions provided the lowest MSE and the highest R^2. The performance criteria of this model were very close to those of the ANN best model; however the ANN model performed slightly better. These results are in agreement with the results of the past studies. Kianpoor Kalkhajeh et al. [38] compared the MLP and ANFIS models for prediction of soil saturated hydraulic conductivity and obtained the best results using MLP models. Azeez et al. [22] declared that the ANN model was performed better than ANFIS model. Noori et al. [23] obtained the more reliable results using ANN model compared to ANFIS model in prediction of carbon monoxide daily concentration.

Sensitivity analysis: In order to assess the predictive ability and validity of the developed models, a series of sensitivity analysis was performed on the best CANFIS and ANN developed networks. 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 model. According to the obtained results in Figure 2, the share of each input item of developed models on output (cucumber yield) can be seen clearly. In both model (ANFIS and ANN) the sensitivity of output to the labor energy is very higher than other inputs, however the sensitivity of ANN model to labor is higher than that of CANFIS model. The second more impressive input is fertilizers in both models. The ANN model has the least sensitivity to the machinery energy, whereas the CANFIS model has the least sensitivity to the electricity. The sensitivity of two models to all inputs, other than pesticides, is relatively similar. In a study carried out by Taki et al. [39] for development of ANN prediction models, the labor energy was reported as the more effective factor on the wheat yield followed by diesel fuel and chemical fertilizer.

Table 3. The measured criteria of different CANFIS models

Inference system	Measured criteria			
Model type	Number of membership functions	Type of membership functions	MSE	R^2
TSK	2	Bell shape	0.0050	0.84
TSK	**3**	**Bell shape**	**0.0046**	**0.86**
TSK	2	Gaussian shape	0.0057	0.81
TSK	3	Gaussian shape	0.0053	0.83

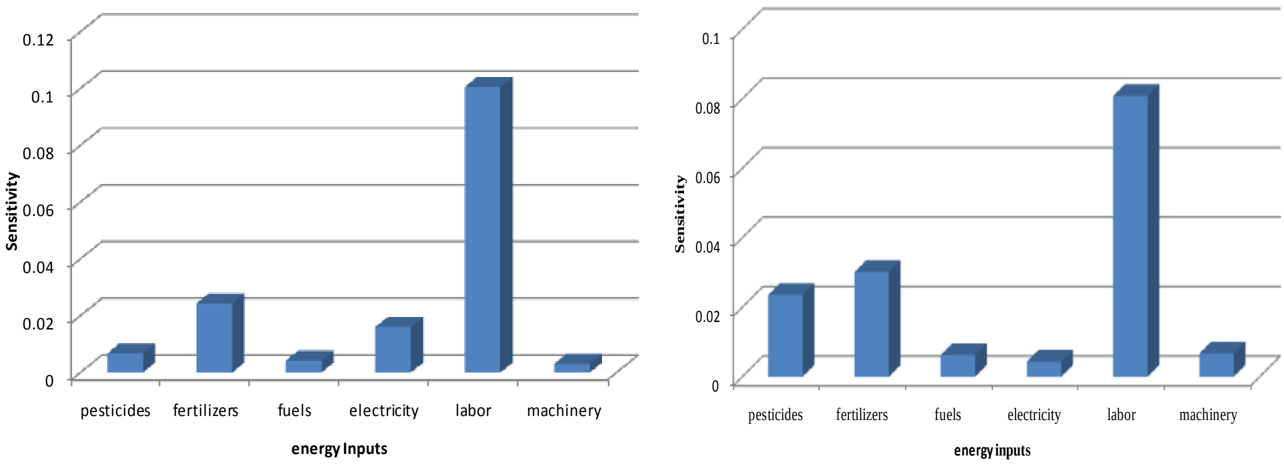

Figure 2. Sensitivity analysis of output yield to energy inputs in the best CANFIS model (right) and ANN model (left)

CONCLUSIONS

In this study, we developed three types of artificial intelligence-based models including two ANN models and one CANFIS models for modeling cucumber yield using energy inputs. We also tested different model structures for each model types and evaluated models using statistical criteria. Study results showed that ANN model with the structure of (6-4-4-4-4-1)-MLP provided the most reliable model; however an CANFIS model developed using three bell type membership functions for each inputs based on TSK inference system also provided reliable outputs. Therefore, these models were selected as the best solution for estimating the cucumber yield in the case study situations. The sensitivity of output yield to the energy inputs in two selected models was relatively similar. In both models the labor was the most effective energy input followed by fertilizer.

REFERENCES

1. Sami, M., Shiekhdavoodi, M. & Asakereh, A. 2011. Energy use in apple production in the Esfahan province of Iran. African Crop Science Journal, 19: 125-130.
2. Shakibai, A.R. & Koochekzadeh, S. 2009. Modeling and Predicting Agricultural Energy Consumption in Iran. American-Eurasian Journal of Agriculture and Environmental Science, 5 (3): 308-312.
3. Asakereh, A., Safaienejad, M. & Sami, M., 2011. Energy and economic analysis of dry farming chickpea in Iran a case study: Lorestan province. Journal of Agricultural Technology, 7(3): 547-555.
4. Ghasemi Mobtaker, H., Keyhani, A., Mohammadi, A., Rafiee, SH. & Akram, A. 2010a. Sensitivity analysis of energy inputs for barley production in Hamedan Province of Iran. Agriculture, Ecosystems and Environment, 137: 367–372.
5. Mousavi Avval, S.H., Rafiee, S., Jafari, A. & Mohammadi, A. 2011. Investigating the energy consumption in different operations of oilseed productions in Iran. Journal of Agricultural Technology, 7(3): 557-565.
6. TaheriGaravand, A., Asakereh, A. & Haghani, K. 2010. Energy elevation and economic analysis of canola production in Iran a case study: Mazandaran province. International Journal of Environmental Sciences, 1(2): 237-242.

7. Taki, M. & Haddad, M. 2012. A novel method with multilayer feed-forward neural network for modeling output yield in agriculture. International Journal of Modern Agriculture, 1(1): 13-23.
8. Firoozi, S., Sheikhdavoodi, M. & Abdeshahi, A. 2012. Energy Auditing and development of economic model for greenhouse cucumber production in Lorestsn and Markazi provinces. Elixir Agriculture, 52: 11680-11686.
9. Ghasemi Mobtaker, H., Akram, A. & Keyhani, A., 2010b. Economic modeling and sensitivity analysis of the costs of inputs for alfalfa production In Iran: A case study from Hamedan province. Ozean Journal of Applied Sciences, 3(3): 313-319.
10. Hassanzadeh Ghorttapeh, H., Taherifard, E. & Gerami, F. 2012. Energy Efficiency in Alfalfa (Medicago sativa L.) Production System in North West of Iran (Case Study: Mahabad City). Annals of Biological Research, 3(5): 2469-2473.
11. Loghmanpour-Zarini, R., Yaghoubi, H. & Akram, A. 2013. Energy use in citrus production of Mazandaran province in Iran. African Crop Science Journal, 21(1): 61–65.
12. Pahlavan, R., Omid, M. & Akram, A. 2012a. The Relationship between Energy Inputs and Crop Yield in Greenhouse Basil Production. Journal of Agricultural Science and Technology, 14: 1243-1253.
13. Mohammadi Farani, S. & Bahrami, H. 2012. Efficiency Evaluation in Bell Pepper Production of Greenhouses in Iran. Journal of Life Science and Biomedicine, 3(1): 69-74.
14. Safa, M. & Samarasinghe, S. 2011. Determination and modeling of energy consumption in wheat production using neural networks: ''A case study in Canterbury province, New Zealand''. Energy, 36: 5140–5147.
15. Sefeedpari, P., Rafiee, S. & Akram, A. 2013. Fossil-based fuels and electricity energy inputs effect on egg production in poultry farms of Iran, Journal of Livestock Science, 4: 1-6.
16. Tabatabaie, S.M.H., Rafiee, Sh., Keyhani, A. & Ebrahimi, A. 2013. Energy and economic assessment of prune production in Tehran province of Iran. Journal of Cleaner Production, 39: 280-284.
17. Khoshnevisan, B., Rafiee, S., Omid, M., Mousazadeh, H. & Rajaeifar, MA. 2014. Application of artificial neural networks for prediction of output energy and GHG emissions in potato production in Iran. Measurement, 123: 120–127.
18. Zangeneh, M., Omid, M. & Akram, A. 2010. A comparative study on energy use and cost analysis of potato production under different farming technologies in Hamadan province of Iran. Energy, 35: 2927–2933.
19. Taki, M., Mahmoudi, A., Ghasemi Mobtaker, H. & Rahbari, H. 2012a. Energy consumption and modeling of output energy with multilayer feed-forward neural network for corn silage in Iran. Agric Eng Int: CIGR Journal, 14(4): 93-101.
20. Pimentel, D. & Hall, CW. 1984. Food and Energy Resource. Academic Press, inc. 512 p.
21. Naderloo, L., Alimardani, R., Omid, M., Sarmadian, F., Javadikia, P., Torabi, M.Y. & Alimardani, F. 2012 Application of ANFIS to predict crop yield based on different energy inputs, Measurement, 45: 1406–1413.
22. Azeez, D., Mohd Ali, M.A., Gan, K.B. & Saiboon, I. 2013 Comparison of adaptive neuro-fuzzy inference system and artificial neutral networks model to categorize patients in the emergency department. SpringerPlus, 2(416); 1-10.
23. Noori, R, Hoshyaripour, GH, Ashrafi, Kh. & Nadjar Araabi, B. 2010. Uncertainty analysis of developed ANN and ANFIS models in prediction of carbon monoxide daily concentration. Atmospheric Environment, 44: 476-482.
24. Kianpoor Kalkhajeh, Y., Rezaie Arshad, R., Amerikhah, H. & Sami, M. 2012b. Comparison of multiple linear regressions and artificial intelligence-based modeling techniques for prediction the soil cation exchange capacity of Aridisols and Entisols in a semiarid region, Australian journal of agricultural engineering, 3(2): 39-46.
25. Areerachakul, S. 2012. Comparison of ANFIS and ANN for Estimation of Biochemical Oxygen Demand Parameter in Surface Water. International Journal of Chemical and Biological Engineering, 6: 286-290.
26. Pachepsky, YaA., Timlin, D. & Varallyay, G. 1996. Artificial neural networks to estimate soil water retention from easily measurable data. Soil Science Society of American Journal, 60: 727–733.
27. Malinova, T. & ZX, G. 2004. Artificial neural network modeling of hydrogen storage properties of Mg-based Alloys. Materials Science and Engineering, 365: 219–227.
28. Kaastra, I. & Boyd, M. 1996. Designing a neural network for forecasting financial and economic time series. Neurocomputing, 10(3): 215– 236.
29. Kanellopoulas, I. & Wilkinson, GG. 1997. Strategies and best practice for neural network image classification. International Journal of Remote Sensing, 18: 711–725.
30. Pahlavan, R., Omid, M. & Akram, A. 2012b. Energy input–output analysis and application of artificial neural networks for predicting greenhouse basil production. Energy, 37, 171–176.
31. Agyare, WA. Park, SJ. & Vlek, PLG. 2007. Artificial neural network estimation of saturated hydraulic conductivity. Vadose Zone Journal, 6: 423–431.
32. Jang, J.S.R., Sum, CT. & Mizutani, E. 1997. Neuro-fuzzy and soft computing, Prentice-Hall, New Jersey.
33. Aziz, K., Rahmana, A., Shamseldinb A.Y. & Shoaibb, M. 2013. Co-Active Neuro Fuzzy Inference System for Regional Flood Estimation in Australia. Journal of Hydrology and Environment Research, 1(1): 11-20.
34. Helsel, ZR. 1992. In: Fluck RC, editor. Energy and alternatives for fertilizer and pesticide use in ''Energy in world agriculture'', Vol. 6. Amsterdam: Elsevier Science Publishing.
35. Sami, M., Shiekhdavoodi, M., Almassi, M. & Marzban, A. 2013. Assessing the sustainability of agricultural production systems using fuzzy logic. Journal of Central European Agriculture, 14(3): 318-330.

36. Rahman, M.M. & Bala, B.K. 2010. Modeling of jute production using artificial neural networks. Biosystems Engineering, 105: 350–356.
37. Rasouli, F., Ajabshirchi, Y. & Taki, M. 2012. Comparison among the Predictions of Energy Consumption for Sugar Beet by Using Artificial Neural Network and Regression Models in Iran, ISESCO Journal of Science and Technology, 8(13): 2-8.
38. Kianpoor Kalkhajeh, Y., Rezaie Arshad, R., Amerikhah, H. & Sami, M. 2012a. Multiple linear regression, artificial neural network (MLP, RBF) and ANFIS models for modeling the saturated hydraulic conductivity of tropical region soils (a case study: Khuzestan province: southwest Iran). International Journal of Agriculture: Research and Review, 2(3): 255-265.
39. Taki, M., Ajabshirchi, Y. & Mahmoudi, A. 2012b. Prediction of output energy for wheat production using artificial neural networks in Esfahan province of Iran. Journal of Agricultural Technology, 8(4): 1229-1242.
40. Jange, J.S.R. 1993. ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans Syst Man Cybern, 23(3): 85-665.
41. Kitani, O. 1999. Energy and Biomass Engineering. CIGR Handbook of Agricultural Engineering. Vol. (V) ASAE. 351p.
42. Verma, SR. 1987. Energy in Production Agriculture and Food Processing. Proceedings of the National Conference held at the Punjab Agricultural University, Ludhana. October 30-31.
43. Cervinka, V.1980. Fuel and energy efficiency. Handbook of Energy Utilization in Agriculture, ed. Pimentel, D. pp. 15–21. Boca Raton, FL: CRC Press.
44. Neurosolutions.2011. Neurosolutions for excel, neurodimension, Inc. <http: //www.neurosolutions.com>.