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Prediction of output energy for wheat production using artificial neural networks in Esfahan province of Iran

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This study was conducted in order to determine the amount of energy consumption for wheat production and comparing artificial neural networks (ANNs) model with regression model for Mahyar plain. For this purpose, the data was collected by completing the questionnaires and interviewing from 100 wheat growing farmers that were selected randomly. The results show that the energy of irrigation has the greatest energy consumption. Energy productivity, net energy gain and energy ratio was 0.048kg/MJ, 79.34GJ/ha and 1.63 respectively. Multilayer perceptron (MLP), RBF Network, self organized map network (SOM) and Generalized feed forward network (GFFN) were examined by changing the number of hidden layers, neurons and training algorithms. Performance of developed ANN model was evaluated with various statistical measures, including the coefficient of determination (R^2) and mean squared error (MSE). It was found that the best network for this study was MLP with 6-8-8-1 topology and LevenbergMarquart (LM) training algorithm by highest R^2= 0.87 and lower MSE=0.027. Quadratic model was the best model, between linear, quadratic, cubic and exponential functions. Coefficient of determination was estimated 0.808 and it has less accuracy rather than MLP model.

Keywords: Artificial Neural Network, Energy Efficiency, Wheat

Introduction

In order to maximize the efficiency of modern agricultural technology to farms in a target region, the farming system of the region should be first characterized, especially to identify possible resource constraints and to capture the diversity of farming systems (Zangeneh *et al.*, 2010). Currently, agricultural operations have to adapt to a more competitive environment and consequently, use new intelligent technologies (Mahmoud, 2004). Hydroponics and greenhouse production are the way of obtaining profitable crops (Nelson,

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2002). A sustainable crop production system requires keeping a high-quality harvest, while keeping energy and raw material consumption low.

The agricultural sector is an important energy consumer. Farmers have an option for reducing energy use by investing in intelligent systems (Kornerandstraten, 2008).

Wheat is one of the top three most producing cereals in the world, ranks the second place after corn and followed by rice. Winter wheat is one of the most major crops that has been planted in Iran. Planted area was 12.96 million ha in 2005-2006. Cereal planted area was 9.37 (72.28%) million ha, which includes wheat (73.24%), barely (16.73%), paddy (6.73%) and corn (3.12%).- Total harvested cereals in 2005-2006 were 22.40 million tons of which wheat recorded of 65.47% followed by barely (13.20%), paddy (11.66%) and corn (9.67%) respectively (Anonymous, 2007). At least, 40% of Iran's wheat is dry with an average yield of only 0.8 tons ha^{-1}. Even in irrigated farms the average yield of wheat rarely exceeds three tons ha^{-1}, which is low in comparison to the world standards (Anonymous, 2005).

Nowadays, the use of energy consumption prediction systems points out to the use of artificial neural networks (ANNs). Srinivasan *et al.* (1994) used a four-layer multilayer perceptron to predict hourly load in a power system.

Zangeneh *et al.* (2010) developed an Artificial Neural Network model to predict mechanization indices based on energy and power consumption. Results showed that the best model for this study had a 13-4-1 configuration. The values of the optimum model's outputs correlated well, with R^2 of 0.98. Value of MAPE calculated as 0.0001 for best ANN model, which indicate superiority of this model over the prediction models.

Houshyar *et al.* (2010) used ANNs for wheat production in Iran. The best model for this work was GFFN model with one hidden layer and LM training algorithm by R^2=0.95 and RMSE= 0.071.

Many researchers have studied the energy consumption patterns for different crops and situations, because the way of energy consuming and its productivity deserves high attention. Regarding to the energy scarcity and wheat importance in Iran, this study was carried out to develop a best ANN in order to forecast output energy for wheat production in Iran.

Materials and methods

Study Area and Energy Used Assessment

This study was conducted in order to determine the amount of energy consumption for wheat production and develop an ANN to predict output energy in the Mahyar plain in Esfahan province of Iran. The plain is located in the south of Esfahan. The data was collected from 100 wheat growing farmers. For collecting the proper data covering the energy consumption pattern, appropriate questionnaires was designed and completed through face to face interviews.

The amount of different inputs were evaluated per hectare and multiplied by their energy equivalents. The energy equivalents of inputs used in this study are given in Table 1.

Energy efficiency indices calculated as shown below:

Energy Ratio: Energy output/Energy input (1)

Energy Productivity: Grain yield output/energy input (MJkg^{-1}) (2)

Net Energy Gain: Energy output – energy input (MJha^{-1}) (3)

Artificial Neural Network

One type of network sees the nodes as ‘artificial neurons’. These are called artificial neural networks (ANNs). An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through synapseslocated on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain *threshold*), the neuron is *activated* and emits a signal though the *axon*. This signal might be sent to another synapse, and might activate other neurons.

The complexity of real neurons is highly abstracted when modeling artificial neurons. These basically consist of inputs (like synapses), which are multiplied by *weights* (strength of the respective signals), and then computed by a mathematical function which determines the *activation* of the neuron. Another function (which may be the identity) computes the outputof the artificial neuron (sometimes in dependence of a certain *threshold*). ANNs combine artificial neurons in order to process information. Fig.1 shows the structure of natural neurons.

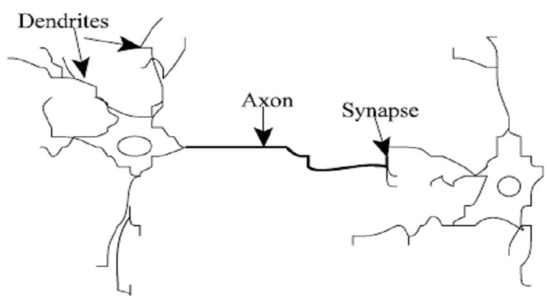

Fig.1. Natural neurons

ANN Topology

In this research, we examined several networks with different architectures using Neuro Solutions 5. General feed forward (GFFN), radial basis function (RBF), self-organizing feature maps (SOM) and multilayer perceptrons (MLP) were examined by changing the number of hidden layer, neurons and training algorithms. Two different algorithms, Momentum and LevenbergMarquart (LM) were used as training algorithms. 50% of collected data in this study was used for training, 25% for cross validation and 25% for test. Energy consumption in the form of machinery, diesel fuel, fertilizer, chemical, seed, irrigation and human power were defined as input columns and output energy was defined as desired output.

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 not change at all in the output value. For this reason, data must be normalized before being presented to the artificial neural network. Data normalization compresses the range of the training data between -1 and 1. The normalization was carried out by the following expression:

$$X_n = \frac{(X - X_{\min}) \times range}{X_{\max} - X_{\min}} + \text{starting value} \tag{4}$$

Where X_n is the value of the normalized data and $X_{\min}$ and $X_{\max}$ are the minimum and maximum of the entire data set, respectively (Perea *et al*., 2009). In this research, the activation function used is a hyperbolic tangent that has the form of:

$$F(net) = \frac{e^{n} - e^{-n}}{e^{n} + e^{-n}} \tag{5}$$

Coefficient R^2 is a measurement of the correlation between observed and predicted values and mean square error (MSE) was calculated for each model by the following equation:

$$MSE = \frac{\sum_{i=1}^{n} \left(y_{oi} - y_{pi} \right)^2}{n} \tag{6}$$

Where y_{oi} is the observed value, y_{pi} is the predicted value and n is the total number of generalized samples.

Multilayer perceptrons (MLP) are layered feed forward network typically trained with static back propagation. Their main advantage is that they are easy to use, and that they can approximate any input/output map (Houshyar *et al.*, 2010).

Generalized feed forward networks are a generalization of the MLP such that connections can jump over one or more layers. In practice, however, generalized feed forward networks often solve the problem much more efficiently.

Radial basis function (RBF) networks are nonlinear hybrid network typically containing a single hidden layer of processing neurons. These networks tend to learn much faster than MLP.

Self-organizing feature maps (SOM) transform the input of arbitrary dimension into a one or two dimensional discrete map subject to a topological constraint (Houshyar *et al.*, 2010).

Results and disscusion

Energy Consumption Analysis

The inputs used in wheat production, and their energy equivalents are shown in the Table 1. The results revealed that the total energy input for various processes in the wheat production was calculated to be 125674.8 $MJha^{-1}$. Bahrami *et al.* (2011) concluded that the input energy for wheat production was to be 58367.69$MJha^{-1}$. The average inputs energy consumption was highest for irrigation, seed and total fertilizer. Similar results have been reported in the literature that the energy input of chemical fertilizers has the biggest share of the total energy input in agricultural crops production (Tsatsarelis, 1993; Erdal *et al.*, 2007; Uzunoz *et al.*, 2008; Kizilaslan, 2009; Mobtaker *et al.*, 2010; Taki*et al.*, 2012; Monjezi *et al.*, 2011). Consequently, Börjesson and Tufvesson (2011) reported that fertilizers and diesel fuel were the main energy consuming inputs in wheat, sugar beet, canola, maize and willow production.

Table 1. Energy used status for wheat production in Esfahan province

Input	Equivalent (MJ/ha)	Percent of total
Machinery manufacture and depreciation	1332.9	1.06
Fuel consumption	9983	7.9
Irrigation	96885.5	77.1
Human power	378	0.31
Seed, fertilizer, and chemicals	16442.5	13.1
Transportation	643.77	0.51
Total	125674.8	100

Table 1 showed that the highest share of total energy used belongs to irrigation (77.1%). This is due to the high depth of water wells because of underground water resource depletion. Hence, and because of decrease in rainfall and also inefficient use of water through inferior irrigation methods, proper management of water use both in selection of appropriate irrigation methods, and also in irrigation rates and periods is a necessity.

The inputs energy consumption was least for human power (378 $MJha^{-1}$). The share of this input was less than one. Similar results have been reported by researchers (Strapatsa, 2006; Kizilaslan, 2009; Mobtaker *et al.*, 2010). Fertilization usage management and integrating a legume into the crop rotation are energetically favorable to reduce the need for chemical fertilizer. In this region, usage of composts, chopped residues or other soil amendments may increase soil organic matter content and fertility in the medium term and so reduce the chemical fertilizer energy requirements. Also, applying a better machinery management technique, proper tractor selection to reduce diesel fuel requirement or technological upgrade to substitute fossil fuels with renewable energy sources help to minimize the fossil fuel usage and thus to reduce the environmental footprints (Mousavi–Avval *et al.*, 2010).

The energy productivity, net energy gain and energy ratio of wheat production in the Esfahan province are listed in Table 2. The energy ratio was calculated 1.63 which is often used as an index to examine the energy efficiency in crop production (Kuesters and Lammel, 1999). The energy ratio for some crops are reported as 2.8 for wheat, 4.8 for cotton, 3.8 for maize and 1.5 for sesame (Canakci *et al.*, 2005), and 1.25 for potato (Mohammadi *et al.*, 2008). The energy productivity (grain) of wheat production was calculated as 0.048 kg MJ^{-1}. The net energy of wheat production was found to be 79.34MJ ha^{-1}. It indicates that in this crop production energy is gained (net energy is greater than zero). In literature, similar results have been reported (Nguyen and Haynes, 1995; Mandal *et al.*, 2002; Erdal *et al.*, 2007; Esengun *et al.*, 2007; Mobtaker *et al.*, 2010). Bahrami *et al.* (2011) studied energy productivity, energy ratio and net energy for wheat, which amount of above indices were reported as 0.052 $kgMJ^{-1}$, 1.51 and 63.2 GJ, respectively.

Table 2. Energy indicates for wheat production in Mahyar plain

Parameter	Unit	Amount
Energy productivity (grain)	$KgMJ^{-1}$	0.048
Net energy gain (grain)	GJ	-35.57
Net energy gain (grain and straw)	GJ	79.34
Energy ratio (grain)	-	0.717
Energy ratio (grain and straw)	-	1.63

ANN Energy Prediction

The results of test corresponding to some network configurations are shown in Table 3. It was found that LevenbergMarquart (LM) was better than Momentum training algorithms for most of networks in this study. The structure of the best MLP network use in this research is shown in Fig.2. As it can be seen in Table 3, the best performance was achieved by MLP with 6-8-8-1 topology and LM training algorithm with R^2= 0.87 and MSE= 0.027 (Fig. 3) and then by SOM with 6-9-9-1 topology and LM training algorithm with R^2= 0.85 and MSE= 0.039 then, by GFFN with 6-8-8-1 topology and LM training algorithm with R^2= 0.83 and MSE= 0.042 and by RBF with 6-10-10-1 topology and Momentum training algorithm with R^2= 0.82 and MSE= 0.049 respectively. The desired and actual network outputs for these four networks are shown in Fig. 3, 4, 5, and 6 respectively.

Rahman and Bala (2010) reported that a model consisted of an input layer with six neurons, two hidden layers with nine and five neurons and one neuron in the output layer was the best model for predicting jute production in Bangladesh. Mohammadi *et al*. (2010) developed an ANN model between input energies and the yield value of kiwifruit production in Mazandaran province of Iran. They used annual energy consumption per hectare of fruit production by different inputs as input variables and the yield level of fruit as output parameter. From this study they concluded that the ANN model with 6-4-1 structure was the best model for predicting the kiwifruit yield in surveyed region. Pahlavan *et al*. (2012) used Artificial Neural Network model for predicting greenhouse basil production in Iran. Results showed, the ANN model having 7-20-20-1 topology can predict the yield value with higher accuracy. For the optimal model, the values of the models outputs correlated well with the actual outputs, with coefficient of determination (R^2) of 0.976. For this configuration, RMSE and MAE values were 0.046 and 0.035, respectively.

Table 3. Result of tested Artificial Neural Network for energy prediction

Network	Hidden layers	Neurons of hidden	Training algorithm	MSE of training	MSE of cross validation	R^2
MLP	1	5	Mom- LM	0.008- 0.048	0.070 -0.033	57-70
MLP	1	6	Mom- LM	0.006- 0.045	0.138- 0.077	50-52
MLP	1	7	Mom- LM	0.001- 0.046	0.032- 0.064	69-75
MLP	2	8	Mom- LM	0.001- 0.046	0.027- 0.071	57-87
MLP	2	9	Mom- LM	0.004- 0.047	0.040- 0.068	51-53
MLP	2	10	Mom- LM	0.012- 0.044	0.034- 0.067	61-56
SOM	1	5	Mom- LM	0.020- 0.042	0.071- 0.060	54-67
SOM	1	6	Mom- LM	0.010- 0.045	0.057- 0.065	61-70
SOM	1	7	Mom- LM	0.009- 0.042	0.036- 0.059	65-71
SOM	2	8	Mom- LM	0.004- 0.044	0.036- 0.062	69-75
SOM	2	9	Mom- LM	0.008- 0.043	0.039- 0.059	72-85
SOM	2	10	Mom- LM	0.007- 0.044	0.038- 0.060	61-64
RBF	1	5	Mom- LM	0.018- 0.032	0.117- 0.050	71-75
RBF	1	6	Mom- LM	0.016- 0.003	0.075- 0.107	70-72
RBF	1	7	Mom- LM	0.013- 0.033	0.121- 0.052	74-77
RBF	2	8	Mom- LM	0.006- 0.042	0.045- 0.059	65-68
RBF	2	9	Mom- LM	0.001- 0.042	0.053- 0.049	76-72
RBF	2	10	Mom- LM	0.082- 0.042	0.091- 0.049	82-69
GFFN	1	5	Mom- LM	0.011- 0.031	0.053- 0.060	71-73
GFFN	1	6	Mom- LM	0.099- 0.027	0.033- 0.059	77-75
GFFN	1	7	Mom- LM	0.004- 0.027	0.054- 0.047	78-74
GFFN	2	8	Mom- LM	0.004- 0.037	0.042- 0.054	79-83
GFFN	2	9	Mom- LM	0.005- 0.023	0.033- 0.046	65-69
GFFN	2	10	Mom- LM	0.009- 0.022	0.056- 0.049	80-79

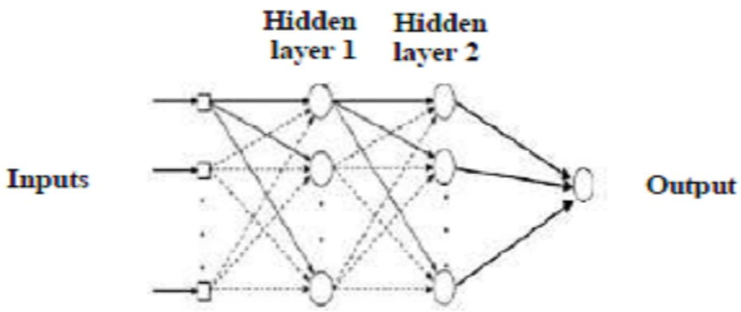

Fig. 2. Structure of MLP network use in this research

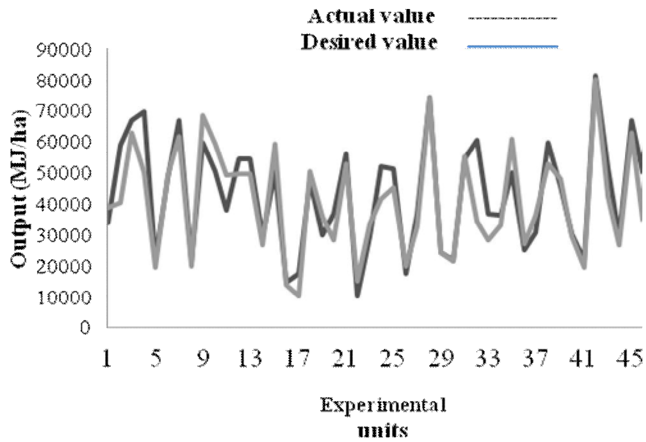

Fig. 3. Desired and actual network outputs for MLP with R^2= 0.87

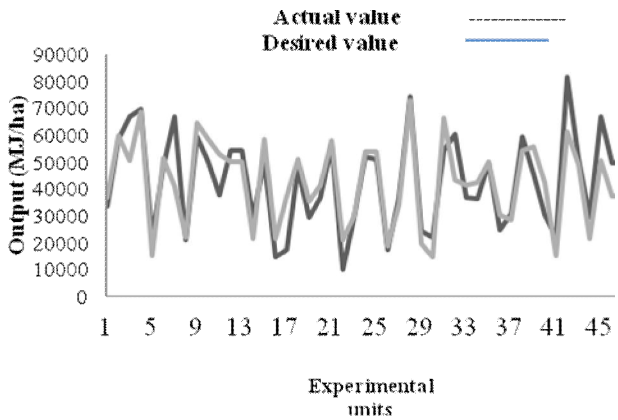

Fig. 4. Desired and actual network outputs for SOM with R^2= 0.85

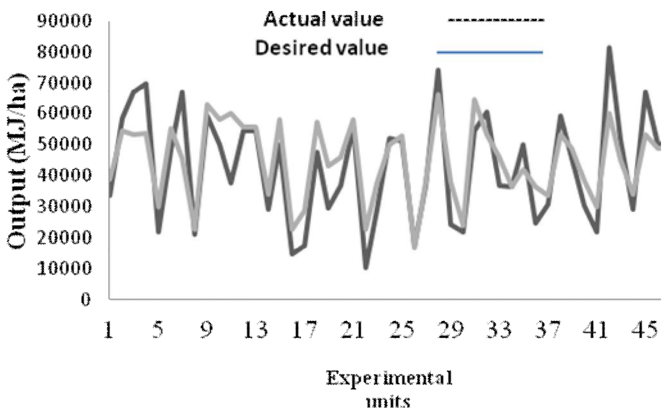

Fig. 5. Desired and actual network outputs for GFFN with R^2= 0.83

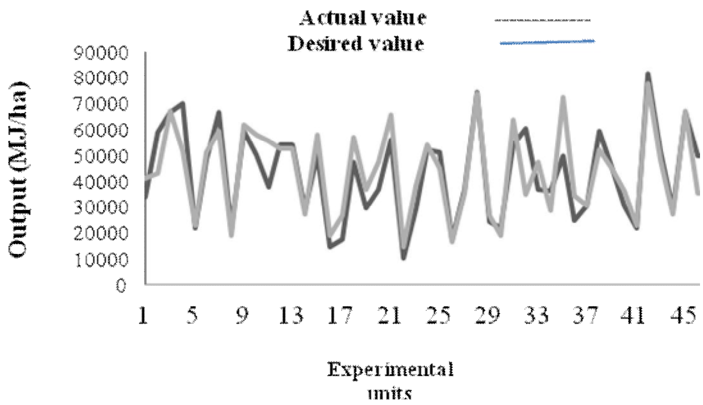

Fig. 6. Desired and actual network outputs for RBF with R^2= 0.82

Sensitivity analysis

In order to assess the predictive ability and validity of the developed models, a sensitivity analysis was performed using the best network selected (Fig. 7). The robustness of the model was determined by examining and comparing the output produced during the validation stage with the calculated values. The MLP model was trained by withdrawing each input item one at a time while not changing any of the other items for every pattern. According to the obtained results in Fig. 6, the share of each input item of developed MLP model on desired output (output energy) can be seen clearly. Sensitivity analysis provides insight into the usefulness of individual variables. With this kind of analysis it is possible to judge what parameters are the most and the least significant during generation of the satisfactory MLP. It is evident that human energy had the highest sensitivity on output (55%), followed by diesel fuel. Furthermore, the sensitivity of irrigation was relatively low. Pahlavan *et al*. (2012) reported that the chemical fertilizer energy had the highest sensitivity on output (basil production), followed by FYM (farm yard manure), diesel fuel and chemicals energies. Also, the sensitivity of electricity, human and transportation energies was relatively low.

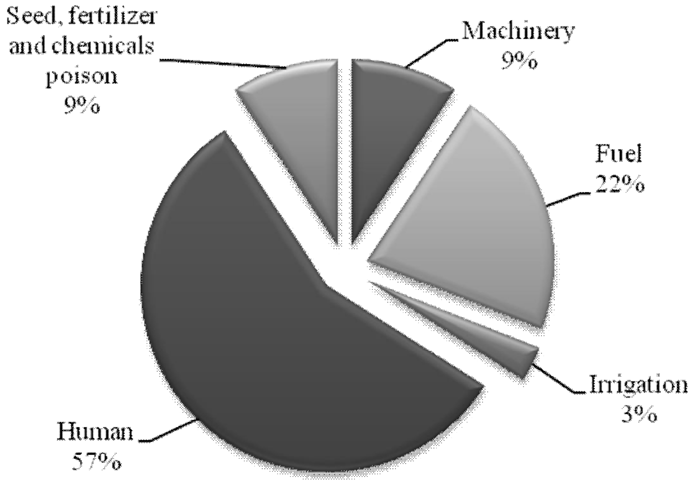

Fig. 7. Sensitivity analysis of input items

Statistical analysis

The results obtained from regression analysis (with the target of testing significant regression coefficient related to desiring models) and corresponding "F" data, also R^2 and modifiedR^2 of each model, are shown in Table 4. Obtained results show that regression coefficient of each model is significant at the probability level of 1%. So these models can be used for predicting output energy for wheat production in Esfahan province. However performances have to be evaluated based on the value of modifiedR^2 , to choose the best model. According to this factor, quadratic model is recommended for predicting output energy in this cultivation.

Table 4. Result of tested regression models for energy prediction

Model	β_1	β_2	β_3	F	R^2	Adjustable R^2
Linear	2.67^{**}	-	-	$1.2\times 10^{3**}$	69.6	69.3
Quadratic	2.43^{**}	0.002^{**}	-	818.77^{**}	81	80.8
Cubic	3.17^{**}	0.007^{**}	$2.1\times10^{-4**}$	577.73^{**}	78.7	78.3
Exponential	4.2^{**}	0.023^{**}	-	689.7^{**}	72.8	72.2
power	1.34^{**}	0.181^{**}	-	824.8^{**}	76	75.7

** Significant at 1% probability level

Explanation: linear model: $y = \beta_1 x$ Quadratic model: $y = \beta_1 x + \beta_2 x^2$

Cubic model: $y = \beta_1 x + \beta_2 x^2 + \beta_3 x^3$ Exponential model: $y = \beta_1 e^{\beta_2(x)}$

Power model: $y = \beta_1 x^{\beta_2}$

Conclusion

This study was conducted in order to determine the amount of energy consumption for wheat production and develop an ANN for predicting output energy in Esfahan province of Iran. Using Artificial Neural Network (ANN) for this prediction revealed that the optimal network for this study were MLP with 6-8-8-1 topology and LM training algorithm with R^2= 0.87 and MSE= 0.027 and then by SOM with 6-9-9-1 topology and LM training algorithm with R^2= 0.85 and MSE= 0.039 then, by GFFN with 6-8-8-1 topology and LM training algorithm with R^2= 0.83 and MSE= 0.042 and by RBF with 6-10-10-1 topology and Momentum training algorithm with R^2= 0.82 and MSE= 0.049 respectively. Furthermore, in this research, quadratic model was the best regression model with the modified determination coefficient of 0.808 but its determination coefficient was less than neural network. Finally, neural network could present a more precise model with its training algorithm.

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