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The Modeling and Comparison of GMDH and RBF Artificial Neural Networks in Forecasting Consumption of Petroleum Products in the Agricultural Sector

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Abstract

Energy plays a significant role in today's developing societies. The role of energy demands making decisions and policy with regard to its production, distribution, and supply. The vital importance of energy, especially fossil fuels, is a factor affecting the agricultural production.

This factor has a great influence on the production of agricultural products in Iran. The forecast of the consumption of oil products by the agricultural sector can help managers and planners to adopt sound management practices for their consumption. Presently, artificial neural networks are regarded as a powerful tool for the analysis and modeling of nonlinear relationships. The present study employed GMDH and RBF artificial neural networks to estimate the consumption of oil products by the agricultural sector. The underpinning parameters were selected to include the value added to the fixed price, rural population, agricultural land area, agricultural mechanization (tractor), and the consumption rate of oil products, electricity, price of oil products, and total energy use by the agricultural sector for the period of 1967-2017. The comparison of MSE, MAE, and MAPE for the GMDH and RBF models showed that the GMDH neural network was highly capable of modeling the energy consumption of the agricultural sector.

1. Introduction

Among the production factors in the economic systems, energy is such an important factor that all production and service activities are made possible by energy use. Failure to meet energy demand will disrupt economic and social activities (Sardar Shahraki, 2017). Oil price shocks caused oil-exporting countries to suffer from a recession. Therefore, economic analysts have since focused more on explaining the relationship between energy consumption and economic growth. The availability of excessive and inexpensive energy allows its overuse by different sectors including the agricultural sector. Nonetheless, the

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agricultural sector plays a crucial role in Iran's economy. This sector is a strategic sector because of the need for its products (Mousavi et al., 2010), reflected in its 10.7% contribution to GDP, the recruitment of 18% of all employed workforce, and 30% contribution to non-oil exports.

Among the different types of energy carriers, two carriers of oil products, i.e. oil and gas, account for about 69% of the total energy consumption. Also, electricity, with about 29% of share, is the second largest source of energy used in the agricultural sector. The final value of energy consumption by this sector over the past decade has always been less than 7% of the final energy consumption of whole Iran (with an average share of about 5%) (Ghasemi, 2012).

The government of Iran has launched initiatives for more efficient use of energy resources in recent years and the agricultural sector has been no exception. In addition, environmental concerns have directed the attention toward curbing the application of off-farm inputs, especially energy.

The prediction of the consumption of oil products by agriculture can enable both managers and planners to manage their use in a sound way. It is of crucial importance in several aspects to know the amount of energy carriers consumed by the agricultural sector in the future so that this sector will find it necessary to find an efficient way to predict their use. Firstly, energy is an important input to production. Thus, as the production sector is commercialized more, it becomes more energy-dependent and energy will play a more important role in the production. Secondly, the awareness of the energy consumption rate can be useful in adopting more appropriate environmental policies.

Furthermore, this awareness can help the formation of macro policymaking for the agricultural sector (Taheri & Mousavi, 2010). There are numerous methods to predict time series variables. Economists usually use econometric methods to estimate the demand function. In general, the prediction methods can be divided into two classes: Linear and nonlinear. The application of nonlinear models has been considerably augmented among economists owing to the significant development of fast data processing by electronic machines. A well-known example of these methods is the neural networks model the application of which was introduced into macroeconomics in the 1990s. Presently, artificial neural networks are deemed to be powerful tools to analyze and model nonlinear relationships.

In this paper, first, the relevant literature is reviewed. Then, the MATLAB software package is used to model artificial neural networks, estimate radial basic function (RBF), and group method of data handling (GMDH) models. Also, the consumption of petroleum derivatives by the agricultural sector is predicted on the basis of the data collected for the 1967-2017 period. The paper ends with some final conclusions and comments.

2. Literature Review

Research already done on the prediction of time series has always drawn attention to itself. The methodology used and motivations behind tracking such time series have evolved over the course of time. The research on the prediction of consumption commenced with the application of multiple regression analysis and time series models. Overall, expert systems are highly capable of modeling natural systems. They have widely been utilized in different fields of basic and engineering science including the agricultural sector. Interests have been aroused in recent years for the use of expert systems, especially artificial neural network, in predicting the time series. Some relevant studies are reviewed below.

Alam et al. (2005) studied energy flows in Bangladesh during 1980-2001. The energy forms that were addressed included human and animal energy, machinery, electricity, gasoline, fertilizers, and chemical pesticides. The results of the study showed that energy efficiency, i.e. the ratio of energy consumption to energy data, decreased from 11.28% to 1.8%. As a result of the energy intake, energy had been accelerated faster than energy consumption, resulting in the loss of energy efficiency.

In an attempt to predict the energy demand of the transportation system in Iran using the artificial neural network and considering the socio-economic parameters for the period of 2007-2021, Menhaj et al. (2010) used feed-forward supervised neural network to forecast and report the back-propagation algorithm for the training of the networks. The results of the forecast showed much lower error when compared to those gained from multivariate regression.

Mousavi et al. (2010) focused on forecasting the consumption of energy products by the agricultural sector in Iran. They stated that the subsidy reform program had been influential on energy consumption. In this regard, they used the ARIMA and ARCH models to predict the consumption of energy carriers (oil and power products) in the agricultural sector. They reported a slight increase in the consumption of the aforementioned energy carriers in the sector studied. The prediction error of the ARIMA model was lower in all series than that of the ARCH model except for the consumption of oil products.

In a study done on the use of artificial neural network and time series to forecast the electricity consumption of the agricultural sector, Ebrahimi (2012) found that three-layer perceptron neural network with back-propagation algorithm training method had a MAPE of 1.02%, which was lower than that (1.13%) of time series model. Other error parameters showed similar results. Accordingly, the neural network was found to be more capable of predicting electricity consumption in the agricultural sector than the ARIMA model.

Sadeghi et al. (2013) attempted to predict long-term demand for electricity using a hybrid method of particle swarm optimization (PSO) and adaptive neuro-fuzzy inference system (ANFIS). Their results confirmed the high capability of the PSO-ANFIS hybrid model in forecasting the long-term demand for electricity. According to the most likely scenario, the demand for electricity in Iran was estimated at 401 billion kWh in 2025. Also, they claimed that the hybrid method was more efficient in predicting the independent variables than the ARIMA linear model.

In a study to forecast energy consumption in the agricultural sector, Abbasi (2015) first predicted the sector's value added with an ARIMA model. Then, he calculated the average energy intensity of the study period (7.0). Moreover, he defined scenarios for the variation of future energy intensity including a reference scenario, three optimal scenarios, and two non-optimal scenarios. On this basis, he predicted the energy consumption rate of the agricultural sector up to 2031. Considering the social cost of the excessive growth of energy consumption, it could be observed that if energy saving programs are not implemented purposefully, the environmental degradation induced by higher greenhouse gases emission will extend.

Barthelmie et al. (2008) focused on the economic benefits of short-term forecasting for wind energy in the UK electricity market. Accordingly, they reported that this forecast depended on the precision. Also, the prediction of electricity purchase price and short-term forecasts were important for both wind farm owners and transmission/distribution operators.

Predicting the energy consumption of buildings, Li and Su (2010) stated that there were diverse ways to forecast a building's energy consumption including simple regression. They proposed a novel method, i.e. a hybrid genetic algorithm-hierarchical adaptive network-based fuzzy inference system (GA-HANFIS) model, to forecast air conditioning consumption of a hotel on a daily basis for over three months. It was reported that the GA-ANFIS model outperformed NNS in terms of prediction accuracy.

In another study, the prediction of nonlinear energy consumption series was investigated using a hybrid dynamic model. In this regard, Lee and Tong (2012) stated that although traditional statistical models may perform accurately in predicting energy consumption, they may suffer from such limitations as the need for a large database and the assumption of a linear formula. In their study, the new hybrid dynamic approach is a mixture of a dynamic grey model and genetic programming for energy consumption forecast. This method is suggested because of its excellent accuracy and applicability with limited databases.

Pukšec et al. (2013) forecasted long-term energy demand of the transport sector in Croatia up to 2050. They used a developed and tested simulation model. Their analysis revealed that considerable saving could be attained by improving energy efficiency and electrifying personal vehicles fleet, thereby reducing the energy consumption by half.

Abbasi (2015) estimated the amount of energy consumption in Iran's agricultural sector using the ARIMA model. He predicted two satisfactory scenarios and two unsatisfactory scenarios of energy consumption by 1410. Taking into account the social costs caused by the excessive consumption of energy, it could be seen that if energy saving plans are not intentionally implemented, annual economic losses will increase due to the high energy consumption by this sector. In addition, environmental degradation will be aggravated by the increased level of greenhouse gas emissions. The same is also true for the energy consumption of sources of energy which are subsidized.

Kaytez et al. (2015) used the new methods of support vector machines (SVMs), least squares support vector machines (LS-SVMs), and artificial neural networks to forecast the electricity consumption in Turkey. The independent variables included gross electricity generation, installed capacity, number of subscribers, and population. The prediction by various performance criteria showed that LS-SVM was the more accurate and faster forecasting model.

Wang et al. (2017) studied rural energy consumption in China. They reported that rural households with higher income preferred commercial energies (e.g. electricity and liquefied petroleum gas) to such energies as straw and wood. Contrary to this, the latter was still the main energy source for Chinese rural families.

As it can be noticed, due to the importance of energy, numerous studies have focused on the forecast for energy consumption. Literature review implies that the use of expert and non-regression systems, especially artificial neural networks, to predict time series has drawn more attention in recent years than regression models. Therefore, in this study, artificial neural networks RBF and GMDH were applied to model and predict energy consumption by the agricultural sector in Iran. One of the strengths of this research was the use of two different types of artificial neural network structures and the comparison of their outputs, higher diversity, and differences in the structures and model parameters.

3. Theoretical Framework and Methodology

The present paper used GMDH and RBF neural networks in order to construct models to forecast the use of petroleum products by the agricultural sector. The data included the consumption rate of the petroleum products, electricity, the price of oil products, and the total energy in the agricultural sector derived from Energy Balance Sheet of the Iranian Ministry of Energy, the agricultural sector's value added to the fixed price, rural population taken from the Central Bank, and the agricultural land area and agricultural mechanization (tractor) derived from the World Bank for the period of 1967-2017. The choice of input data was based on a review of the literature (Taghizadeh Mehrjerdi et al., 2015).

3.1 GMDH Neural Network

GMDH neural network is a set of neurons constructed by the connection of different pairs via a quadratic polynomial. The network combines quadratic polynomials generated for all neurons in order to describe an approximate function $\hat{f}$ with the output $\hat{y}$ (consumption of oil products by the agricultural sector) for a set of inputs $X = (x_1, x_2, x_3, \dots, x_n)$ (consumption of oil products in the previous period, energy consumption, electricity consumption, agricultural land area, rural population, agricultural mechanization, agricultural value added, and oil products prices) with the lowest error compared to the actual output *y* (Atashkari et al., 2007). Therefore, the actual results for M laboratory data including *n* inputs and one output can be depicted as in Equation (1).

$$y_i = f(x_{1i}, x_{2i}, x_{3i}, \dots, x_{ni}) \quad ; \quad i = 1,2, \dots, M \tag{1}$$

Here, the model seeks a network that can predict the output value $\hat{y}$ for each input vector *X* using Equation (2)

$$\hat{y}_i = \hat{f}(x_{1i}, x_{2i}, x_{3i}, \dots, x_{ni}) \quad ; \quad i = 1,2, \dots, M \tag{2}$$

so that mean square error is minimized between the actual values and the predicted values. In other words:

$$MSE = {\sum_{i=1}^{M} (\hat{y}_i - y_i)^2}/{M} \quad \longrightarrow \quad Min \tag{3}$$

The general form of the connection between input variables and output can be expressed by a polynomial function as in Equation (4).

$$y = \alpha_0 + \sum_{i=1}^{n} \alpha_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_{ij} x_i x_j + \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} \alpha_{ijk} x_i x_j x_k + \cdots \tag{4}$$

This is called Ivakhnenko polynomial. In most practical cases, the quadratic two-variable form of this polynomial is used as follows (Ivakhnenko & Müller, 1995):

$$\hat{y} = G(x_i, x_k) = \alpha_0 + \alpha_1 x_i + \alpha_2 x_j + \alpha_3 x_i^2 + \alpha_4 x_j^2 + \alpha_5 x_i x_j \tag{5}$$

The unknown coefficient α_i in Equation (5) is estimated by regression techniques so as to minimize the difference between the actual output *y* and its predicted value $\hat{y}$ for each pair of the input variable x_i, x_j.

A set of polynomials is constructed by Equation (5) whose unknown coefficients are obtained by the least squares method. For each function G_i (each generated neuron), the coefficients of the equations for each neuron are obtained so as to minimize its total error in order to optimally fit the inputs in the whole set of input-output pairs (Ibid):

$$E = {\sum_{i=1}^{M} (y_i - G_i)^2}/{M} \quad \longrightarrow \quad Min \tag{6}$$

In basic forms of the GMDH algorithm, all binary compounds of neurons are constructed out of *n* input variables and the unknown coefficients of all neurons are estimated by the least squares methods. Thus, $\binom{n}{2} = \frac{n(n-1)}{2}$ neurons are constructed in the second layer which can be displayed as in Equation (7):

$$\left\{ \left(y_i, x_{ip}, x_{iq}\right) \middle| (i = 1,2, \dots, M) \& \;\; p, q \in (1,2, \dots, M) \right\} \tag{7}$$

The quadratic form of the function expressed in Equation (5) is used for each triple M rows. These equations can be represented in matrix form as in Equation (8):

$$A\alpha = Y \tag{8}$$

in which A denotes the vector of the unknown coefficient of the quadratic equation shown in Equation (5).

$$\alpha = [\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5] \quad (9)$$

$$Y = [y_1, y_2, y_3, \dots, y_M]^T \quad (10)$$

It is readily observable from the values of input vectors and the function forms that:

$$A = \begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}^2 & x_{1q}^2 & x_{1p}x_{1q} \\ 1 & x_{2p} & x_{2q} & x_{2p}^2 & x_{2q}^2 & x_{2p}x_{2q} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{Mp} & x_{Mq} & x_{Mp}^2 & x_{Mq}^2 & x_{Mp}x_{Mq} \end{bmatrix} \quad (11)$$

The least squares method of multiple-regression analysis solves the equations as manifested in Equation (12).

$$\alpha = (A^T A)^{-1} A^T Y \quad (12)$$

This equation constructs the coefficient vector of Equation (5) for the whole set of triple M's.

The coefficients of the neurons in hidden layers and output are determined at modeling (training) phase on the basis of the initial definition of significance level and confidence interval intended by the researcher. The process of optimizing the coefficients and equations of the neurons and data screening mechanisms, i.e. the exclusion of the lowly-correlated variables, are performed by the genetic algorithm. Therefore, the high-volume calculations are made possible in practice, ergo rendering the normal equations system appropriate and solvable.

3.2 Radial Basis Function

Radial basis function (RBF) network is an example of progressive networks with three layers. The RBF model consists of three layers: An input layer, a hidden layer, and an output layer. Figure 1 displays their general structure (Haykin, 1999).

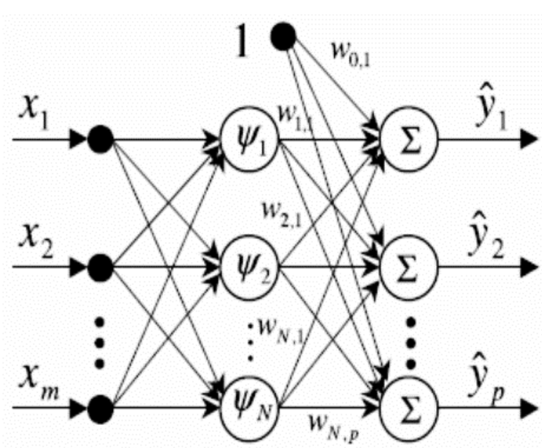

Figure 1. The general structure of the RBF neural network

In this model, the activation function is in a nonlinear and Gaussian form that is defined as below:

$$g(u) = Exp\left(-\frac{1}{2}u_i^2\right) \quad (13)$$

in which u_i denotes the distance of the input vector $X_j = [x_1, x_2, \ldots, x_p]$ from the center vector $C_i = [c_{i1}, c_{i2}, \ldots, c_{ip}]$ with the norm matrix $\sum i$. This is defined as below:

$$u_i = \|X_j - C_i\|_{\sum i} = \sqrt{\sum_{j=1}^{p}\left(\frac{X_j - C_{ij}}{\sigma_{ij}}\right)^2} = \sqrt{\left(\frac{X_1 - C_{i1}}{\sigma_{i1}}\right)^2 + \cdots + \left(\frac{X_p - C_{ip}}{\sigma_{ip}}\right)^2} \quad (14)$$

The norm matrix $\sum i$ with the constant values $[\sigma_{i1}, \sigma_{i2}, \ldots, \sigma_{ip}]$ is considered the parameter of the hidden layer of the *i*th neuron of the RBF network in which the constants are included as the diagonal of the norm matrix. The network output is calculated as follows (Nelles, 2001):

$$y = \sum_{i=0}^{m} W_i Exp\left(-\frac{1}{2}u_i^2\right) \quad (15)$$

Hence, an RBF network entails the three following parameters:

- The output layer weights W_i that are the linear parameters category and specify the degree of diagonality and the height of base functions.
- Processor centers C_i which belong to the class of nonlinear parameters of the hidden layer neurons and specify the location of the base functions.
- Standard deviations σ_{ij} that show the width and extent of the rotation of Gaussian base functions.

In the training of the RBF network, first, the parameters of the hidden layer are calculated by k-means clustering algorithm; then, least squares are employed to calculate the weights of the output layer that is linear.

To compare the predictive capability of RBF and GMDH with the artificial neural network, three criteria were used, as presented in Table 1, to assess the competing models.

Table 1. Criteria to assess the competing models

Criterion	Formula
Mean square error	$MSE = \frac{\sum(\hat{y} - y)^2}{n}$
Mean absolute error	$MAE = \frac{\sum\lvert\hat{y} - y\rvert}{n}$
Mean absolute percentage error	$MAPE = \frac{1}{n}\sum\frac{\lvert y_i - \hat{y}\rvert}{y_i}$

4. Results and Discussion

To identify the factors influencing the consumption of oil products in the agricultural sector, the correlation analysis was performed. Then, the factors exhibiting the highest correlation with the consumption of oil products were selected for the modeling. Table 2 presents the results of the correlation analysis of the parameters.

Table 2. Correlation coefficients for the parameters influencing the consumption of oil products by the agricultural sector over the 51-year period

Parameter	Energy consumption
Consumption of oil products	1.000
Consumption of oil products in the previous period	0.906
Energy consumption	0.928
Electricity consumption	0.703
Agricultural land area	0.608
Rural population	0.872
Agricultural mechanization (tractor)	0.812
Agricultural value added	0.731
Price of oil products	0.122

***Source**: Research findings*

To construct and determine the optimal structure of the artificial neural network models, the input data were divided into three parts: The first part included 70% of data for training, the second part included 15% of data for validation, and the third part included the remaining 15% of data for testing. The models were simulated in the MATLAB software package. In these files, first, the suitable structure was determined in terms of the number of neurons. After determining the suitable number of neurons, the other parameters of the optimal neural network were derived, and all calculations were performed on the basis of this optimal network.

After the number of optimal input neurons was specified, different networks with different neuron numbers were designed and trained to select the number of neurons for the hidden layer of the network. To find out the optimal structure of GMDH model with a linear and nonlinear output, we first began with a simple structure and the neurons of the hidden layer were increased through one-by-one fixed training steps. According to the results presented in Table 3, different structures containing different number of neurons and hidden layers were examined by MSE criterion to select the optimal network, i.e. the network with the least mean square error that had three input neurons and three hidden layer neurons. Therefore, the GMDH neural network could produce the best estimation for the consumption of the agricultural sector for the oil products. The comparison of the linear and nonlinear functions revealed that in the output layer of the GMDH neural model, the nonlinear activity functions outperformed the linear functions.

Table 3. The comparison of the results derived from different models of GMDH neural network

GMDH network	Neuron arrangement	MSE	MAE	MAPE
Model 1	1-3-3 linear	6.44	6.89	3.45
Model 2	3-3-3 linear	5.63	5.96	4.71
Model 3	2-4-5 linear	4.09	4.56	3.58
Model 4	3-5-4 nonlinear	2.63	3.01	2.20
Model 5	3-2-8 nonlinear	2.07	2.72	2.65
Model 6	3-4-6 nonlinear	1.89	2.54	2.11
Model 7	1-3-3 nonlinear	1.09	1.72	1.96

***Source**: Research findings*

As shown in Figure (2), the consumption of oil products estimated by the model is close to actual consumption, with the actual and projected oil consumption being consistent in most cases.

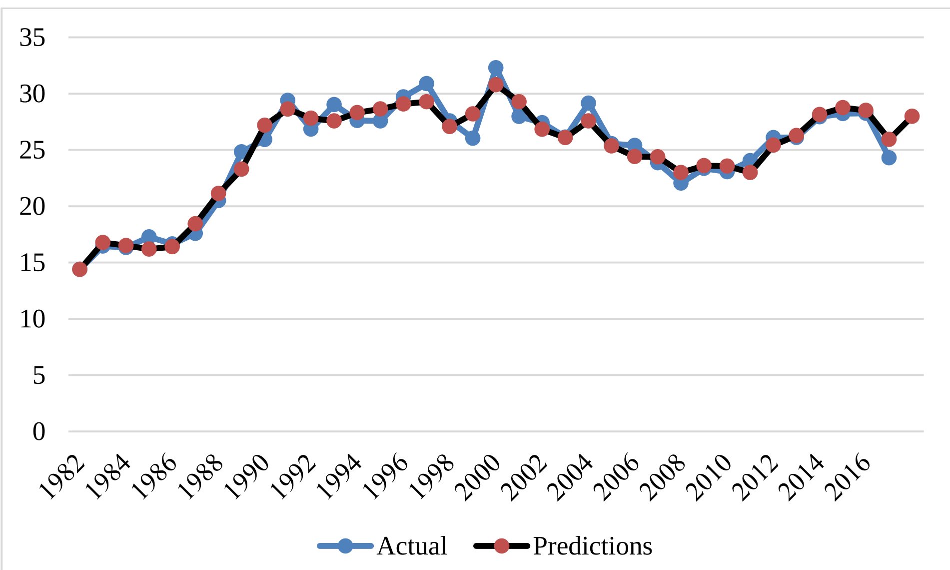

Figure 2. The expected and actual consumption of oil products by the agricultural sector as estimated by the GMDH model

To determine the appropriate structure for the RBF network, the error criterion diagram was drawn for training, testing, and validating datasets. The suitable number of neurons was considered to be the number in which all the three errors decreased proportionally. Given how errors are changed in terms of the neuron number, the appropriate neuron number in the RBF network was selected to be 4. Also, since in this neural model all data were used at once by the clustering method and least squares with linear estimation; thus, the number of training steps was useless. Figure 3 depicts the results of the predicted and actual values of the agricultural sector's consumption of oil products using the RBF model.

Table 4. The comparison of the results derived from different models of RBF neural network

RBF network	Neuron arrangement	MSE	MAE	MAPE
Model 1	1-1-11-2	4.22	4.64	4.87
Model 2	1-1-10-5	3.41	4.89	3.83
Model 3	1-1-5-3	3.20	4.01	3.42
Model 4	1-1-4-3	3.05	4.56	3.76
Model 5	1-1-4-4	3.01	3.29	3.99
Model 6	1-1-2-2	2.98	3.12	2.85
Model 7	1-1-4-2	1.68	2.09	2.02

***Source**: Research findings*

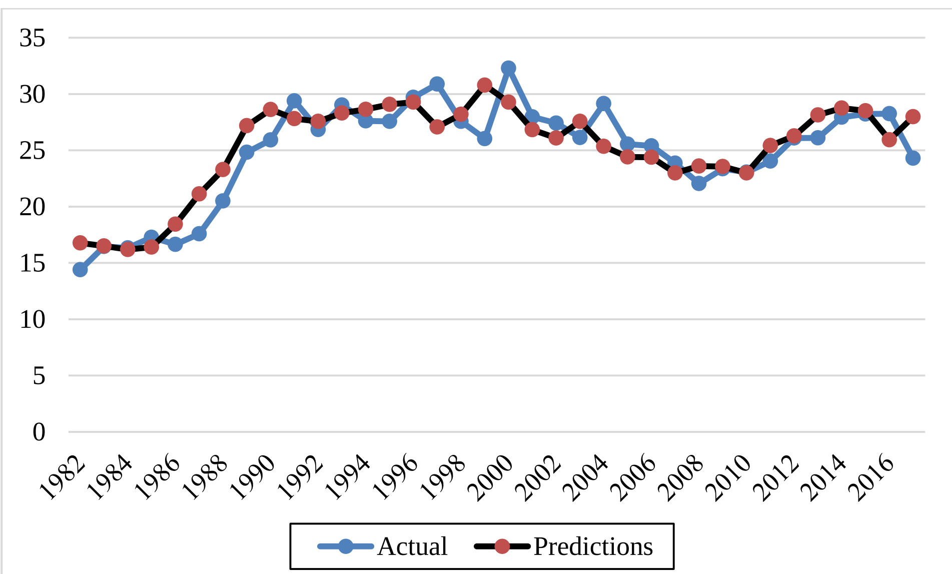

Figure 3. The expected and actual consumption of oil products by the agricultural sector as estimated by the RBF model

Table 5 summarizes the performance of the optimal GMDH and RBF models in forecasting the consumption of oil products by the agricultural sector in terms of MSE, MAE, and MAPE criteria.

Table 5. The comparison and evaluation of the prediction potential of the GMDH and RBF optimum models

Model	Optimum model	MSE	MAE	MAPE
GMDH neural network	1-3-3 nonlinear	1.09	1.72	1.96
RBF neural network	1-1-4-2	1.68	2.09	2.02

***Source**: Research findings*

The comparison of the results in Tables 5 and 6 shows that although both types of the neural network models were highly capable of forecasting the consumption, the explored criteria revealed that the GMDH model outperformed the rival model in predicting the consumption of oil products in the agriculture sector.

Table 6. The results of the selected model using the GMDH and RBF models to predict the consumption of oil products by the agricultural sector

Year	Actual values	GMDH model		RBF model	
		Predicted values	Residual	Predicted value	Residual
1996	27.415	26.386	1.029	26.075	1.34
1997	29.139	26.771	2.368	26.685	2.454
1998	29.155	27.501	1.654	27.028	2.127
1999	25.559	25.411	0.148	23.506	2.053
2000	25.395	24.296	1.099	24.088	1.307
2001	23.854	24.916	-1.062	25.451	-1.597
2002	22.048	22.632	-0.584	23.278	-1.23
2003	23.364	23.161	0.203	22.970	0.394
2004	23.062	23.075	-0.013	22.513	0.549
2005	24.047	23.178	0.869	23.759	0.288
2006	26.094	25.790	0.304	26.935	-0.841
2007	26.1	26.831	-0.731	25.302	0.798
2008	27.945	28.751	-0.806	28.100	-0.155
2009	28.23	28.415	-0.185	25.138	3.092
2010	28.26	28.555	-0.295	26.034	2.226
2011	24.302	25.982	-1.68	26.914	-2.612
2012	24.2	26.236	-2.036	27.672	-3.472
2013	23.5	25.154	-1.654	27.534	-4.034
2014	21.1	23.613	-2.513	26.051	-4.951
2015	-	24.580	-	-	-
2016	-	25.853	-	-	-
2017	-	26.140	-	-	-
2018	-	28.303	-	-	-
2019	-	28.006	-	-	-
2020	-	30.624	-	-	-
2021	-	30.128	-	-	-

***Source**: Research findings (Unit: Million barrels of crude oil)*

On the other hand, although neural networks can model the nonlinear relationships when compared to the ordinary regressions, they are not appropriate to be used for the interpretation of the relationships between the variables. It is noteworthy that neural networks are called black boxes because they do not show the relationship between the variables. Although in GMDH neural network the relationships between the inputs and output can be expressed by neurons equations, these relationships will have no interpretation.

5. Conclusion

In economic discussions, in addition to labor and capital inputs, energy is also considered as one of the major inputs of production. In addition to other factors of production, it has a decisive role in the economic sector of the countries. Energy is one of the factors used in most economic activities. Considering the nature of various activities in the agricultural sector, the most important energy carriers in this sector are petroleum products. Accordingly, it is imperative that economic policymakers have an understanding of the process of how these products are consumed.

In this study, according to the reviewed literature on the accuracy of artificial neural network models in the structural and regression models, artificial neural networks RBF and GMDH were used to forecast the amount of the consumption of oil products by the agricultural sector. The annual data for the consumption of petroleum products in the agricultural sector was the output variable of forecasting models, and the annual data for the consumption of oil products in the previous period, energy consumption, electricity consumption, agricultural land area, rural population, agricultural mechanization, agricultural value added, and the prices of petroleum products were used as the input variables for the prediction models. The results showed that in all of the evaluation indicators and the constructed models, the GMDH artificial neural network outperformed the RBF neural network. The study of seven different structures with different numbers of neurons and hidden layers showed that the GMDH neural network with three layers of latency with one neuron in the first layer, three neurons in the second cavity layer, and three neurons in the third cavity layer yielded the best results for the prediction of the consumption of oil products by the agricultural sector. According to the comparison of linear and nonlinear activity functions, nonlinear functions in the output layer of the GMDH and RBF models performed better than linear functions. Furthermore, among GMDH models, models with nonlinear outputs were more appropriate than linear output models. Larger network structures also showed that they had little effect on improving the results.

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