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The Prediction of Energy Consumption Using Multivariate Regression and Artificial Neural Networks Models (Case Study: Agricultural Sector of Iran)

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ABSTRACT

Awareness of energy consumption in agricultural sector of each country can provide useful guidelines for planning general and Macro policies in this section. Therefore, authorities in each country must attempt to make a more accurate prediction of the energy consumption in this sector and correct planning in consumption in order to effectively control energy demand and supply parameters in agricultural sector. The objective of the present study is to employ multivariate regression and artificial neural networks models for prediction of the energy demand of the agricultural sector in Iran. Therefore, the annual data on energy consumption of the agricultural sector was used as the output variable of the predictive models. On the other hand, the annual data on the total population of Iran and the total products of the agricultural sector were used as the input variables of predictive models. Finally, the relative standard error (RSE), mean error (ME) and relative mean square error (RMSE) were used to compare the results predicted by the neural network and multivariate regression models. The results of evaluations showed that the neural networks model has higher accuracy than the regression model for energy demand prediction.

KEYWORDS: Energy Consumption, Multivariate Regression, Artificial Neural Networks, Agricultural Sector of Iran.

1. INTRODUCTION

Among the different economic sectors, the agricultural sector always allocates itself the lowest share of energy consumption. In 1967, the energy consumption in this sector was 2.8 million barrels. In 1978, it reached to 12.2 million barrels which shows an average annual growth of about 41.51 percent in this period. The growth of energy consumption during 1978-1989 and 1989-1996 was 8.2% and 1.7%, respectively.

In 1996, the energy consumption in the agricultural sector was 30.8 million barrels which reached to 26.8 million barrels in 2006. The average annual growth in this period was 1.98% (Armen and Zare, 2009). However, awareness about the energy carriers' consumption in agricultural sector in the future is important from several points of views. The investigation of the proper method makes the prediction of energy consumption a necessity.

Firstly, following getting more commercialization of the agricultural sector, the dependence on the energy as an important production factor is becoming more significant and it will play a key role in production. Another issue is environmental considerations which have been received more attention recently. It is expected that knowledge of the energy consumption will be effective in the context of adopting more appropriate environmental policies. Moreover, awareness of energy consumption may provide useful guidelines in planning of general policies of the agricultural sector (Mousavi et al, 2011).

Therefore, the Iranian authorities must attempt to effectively control the parameters of energy demand and supply in agricultural sector by accurately predicting the energy consumption in this sector. Nowadays, the use of smart technologies to solve complex practical problems have been received much attention in various industrial sectors. These systems learn the general rules by calculation based on experimental data and thereby they are called intelligent systems. Artificial neural networks are intelligent systems which transfer the hidden knowledge behind the data to the network structure by processing the experimental data. The biggest advantage of the neural networks is their ability to model complex nonlinear relationships regardless of the previous assumptions.

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Section 2 reviews the research background. The theoretical fundamentals are presented in Section 3. Section 4 describes the methodology of the research. Then, in section 5 the research findings are discussed. The conclusions and suggestions are presented in the final section.

2. Background

Due to the successful performance, the neural networks have been used in the field of model detection and identification in many prediction problems. Typically, the following can be mentioned:

Naseri and Kouchakzadeh (2008) presented a model based on experimental design technique for optimal design of neural network architecture with supervised learning considering the interaction between the aforementioned factors. In this paper, the proposed model for the design of neural network architecture to predict the total gasoil consumption. A neural network model was developed to predict gasoil consumption in order to compare the performance of the proposed model using trial and error as one of the traditional methods of architectural design. The superiority of the proposed model has been shown. Also, two models have been designed using regression and ARIMA methods to compare the performance of neural networks with statistical methods. The obtained results in the prediction of gasoil consumption in this sector also showed that forecasting by neural networks yields better results.

Abrishami et al (2010) employed the GMDH neural network to predict gasoline prices based on technical analysis rules including short-term and long-term moving averages as input to the network during different market periods. In this study, the neural network predictions had less error and greater accuracy compared to the time series method.

Shakibae et al (2009) attempted to compare the results obtained in each country separately in addition to crude oil production predictions in the efficiency of producer using linear regression and neural networks. Estimations showed that the neural networks provide better predictions than linear regression models.

Azari et al (2008) used the artificial neural networks due to its extraordinary ability to mimic the nonlinear mapping of inputs to outputs for short-term forecasting of the natural gas consumption in Tehran. Comparison of the results obtained from predictions with the real data of gas consumption suggested that the accuracy of the model on daily and monthly gas consumption is about 93 and 99 percent, respectively. Therefore, the developed models are suitable for estimating the gas consumption in Tehran.

PourKazemi and Asadi (2009) addressed the dynamic prediction of crude oil price using artificial neural networks and ARIMA econometric method. The results indicated that the neural networks predictions had lower errors in comparison with ARIMA method.

Menhaj et al (2010) predicted the energy demand in transportation sector during 2007 to 2021 using artificial neural networks with regard to economic and social indicators. They used the feedforward neural networks with the appropriate supervisor for prediction and back-propagation algorithm for training. The results predicted by this method showed a much lower error compared with multivariate regression method so that the mean absolute error percentage decreased from 15 % to 6 %.

Sadeghi et al (2011) modeled and predicted the daily price of OPEC basket of crude oil using artificial neural networks based on price expectations for daily data. The results were compared with the values predicted by ARIMA model based on prediction accuracy measurement criteria. The results showed that the neural network has a better predictive power compared to ARIMA model.

Dashti Rahmatabadi et al (2011) introduced optimal prediction models for the price of Iranian crude oil. The models used for prediction consisted of 4 neural networks models and one regression model (Moving Average Autoregression). The selected networks include back-propagation feed forward network, back-propagation cascade network, back-propagation element network and generalized regression network.

The results indicated that the generalized regression network models and back-propagation cascade network with quasi-Newtonian training function have the best performances for predicting 10 percent of the crude oil price data with an error less than 1 and less than 2 percent, respectively. The back-propagation feed forward network and back-propagation element network with Levenberg Marquardt training function have a better performance to predict 20% of the crude oil price data. In the case of 30% of the data, the feed forward network is more desirable. Moreover, the results showed that with an increase in the percentage of data used for prediction, especially with an increase from 10% to 20%, the accuracy of predictions relatively declines. The accuracy of moving average auto regression is less than the neural network models as well.

Calgira (2000) employed the artificial neural network technique to predict the amount of thermal energy consumption in buildings and energy consumption in an inactive solar building (Jabri and Eniab, 2006). Nasr et al (2003) used the neural networks and back propagation algorithm to predict gasoline consumption in Lebanon.

Murat and Ceylan (2006) predicted the energy consumption in transportation sector of Turkey using a three-layer neural network and back propagation algorithm. They used GDP, population and number of vehicles per km as inputs to the neural network (Shakibae et al, 2009). Sazen et al (2007) proposed a neural network model to predict the consumption of oil products in Turkey. They designed three different models. Finally, a model was selected as the suitable model to predict oil products consumption in Turkey using the error criteria.

The results of Yu et al (2008) also confirm the superiority of the neural network on moving average auto regression for prediction purposes. Generally, it can be said that the use of neural networks for predicting the prices of energy carriers has been further considered. Moreover, its higher accuracy has been emphasized in

comparative studies. Kokarny and Haider (2009) predicted crude oil price for the next three days. They have concluded that a dynamic model with 13 delays is suitable for short-term prediction of crude oil spot price. The prediction accuracy of 78, 66% and 53% has been estimated for one, two, and three days later, respectively.

Accordingly, given the importance of energy, several studies have been conducted on the prediction of energy cost and consumption. Evaluations and predictions have been performed using a special technique in various studies. The research works in this field are divided into two groups: studies with econometric methods and studies with artificial intelligence and neural networks methods. In all these studies, the higher efficiency and accuracy of neural network models have been validated. Therefore, in the present study, the energy demand of the Iranian agricultural sector is predicted using neural network algorithm to investigate the efficiency of this method compared to other methods used for prediction of energy demand.

3. Theoretical Principles

3.1. Artificial Neural Network

A neural network is determined by its architecture, training method, and exciting function. Architecture, determines the pattern of connections among neurons. Network training changes the values of weights and biases (network parameters) in each step in order to minimize the mean square of output error (Vahedi, 2012). Since feed-forward neural networks or Multi-Layer Perceptron (MLP) ANNs is used in engineering applications such as load forecasting, nonlinear control, system identification, and pattern recognition, thus in this paper, multi-layer perceptron network (with four inputs, three outputs and a hidden layer) with back-propagation training algorithm is used. Since, this method is based on error gradient method, differential function is used. Thus, differentiable functions like Sigmoid, hyperbolic tangent must be used and in this case nonlinear sigmoid transformation function is used. Fig. 1 shows the MLP network that is used in this study (Madahi & Salah, 2012):

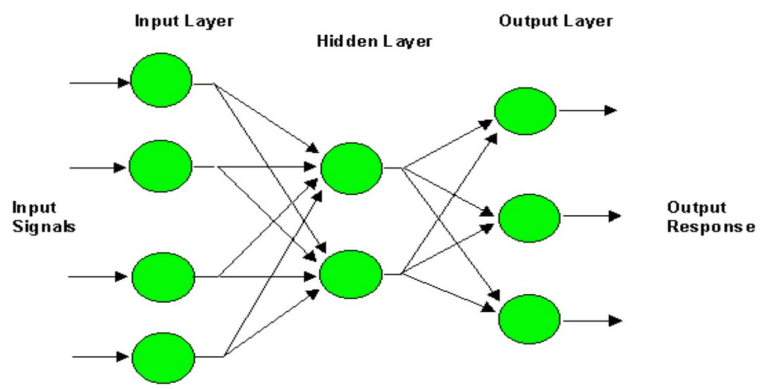

Fig. 1.Artificial Neural Network

3.2. Indices for Evaluation of Models

In this study, the relative standard error (RSE), the mean error (ME), the root mean square error (RMSE) were used to evaluate the performance of neural network/genetics models, artificial neural network and multivariate regression models. The indices are calculated using the following equations (Navabian et al, 2003, Amini et al, 2005):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Z_0 - Z_P)^2} \quad (1) \qquad RSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Z_0 - Z_P)^2}}{Z_{ave}} \quad (2)$$

$$ME = \frac{1}{n}\sum(Z_0 - Z_P) \quad (3)$$

Where Z_0 is the predicted value, Z_p: the observed value, Z_{ave}: the average observed value and n is the number of data.

4. METHODS

Given that the artificial neural networks are data-based models, the data preparation is considered as an important and key step in the use of neural networks. The higher number of data facilitates the approximation of hidden structure in the model. In this study, the annual data on energy consumption of the agricultural sector (including electricity, natural gas and oil products) was used as the output of predictive models. On the other hand, the annual data on the total population of Iran and agricultural products (including agriculture and animal husbandry products) were used as input variables of the predictive models. The time interval of the variables

ranged from 1975 to 2008. 80% of data was used for training and 20 percent were used for testing. It should be noted that the annual data for these variables were collected from the data resources of the Department of Energy and the Central Bank of I.R. Iran. Data analysis was performed using Minitab and Neuro solution.

5. RESULTS

5-1 – The Results of Multivariate Linear Regression

To determine the multivariate regression of the studied parameter, the regression relationship was determined using training data (Equation 5). Then, this relationship was applied on the test data. RMSE, RSE, ME and regression coefficient were obtained equal to 3.2, 0.12, 6.37 and 0.937, respectively. The regression coefficients have a p-value smaller than 0.05 ($p<0.05$). The analysis of variance table was also calculated for the regressions. The results indicate that the fitted equation is statistically significant ($p<0.05$). Finally, the distribution of the error values were calculated which indicating the accuracy of the regression model and the lack of alignment among the input parameters (Table 1).

Table 1 – The results of ANOVA

References	Degree of Freedom(DF)	Sum of Squares	Squares Mean	F-Fisher	p-value
Regression	2	1676.49	838.25	94.38	**<0.05**
Residual	32	284.19	8.88		
Total	34	1960.68			

$$y = -3.13 - 0.000343\,X1 + 0.000759\,X2 \qquad (4)$$

Where Y represents the amount of energy demand in the agricultural sector, X1 indicating the amount of agricultural products and X2 is the representative of the entire population of Iran.

5-2 – The Results of Neural Network

In this study, the network was identified with one hidden layer with sigmoid activation function in the hidden layer and linear activation function in the output layer. The number of neurons varied from 2 to 10 neurons and the number of neurons was determined by trial and error. Also, due to the high efficiency, simplicity and speed, the Levenberg Marquardt training algorithm was used. For predicting energy consumption, the network inputs consisted of the population of Iranian people and the amount of the products of agricultural sector. The root mean square error (RMSE), relative standard error (RSE), the mean error (ME) and regression coefficient of the energy demand of the agricultural sector was obtained equal to 2.01, 0.07, 3.01 and 0.94, respectively.

$$f(x) = \frac{1}{1+e^{x}}$$

5-3 – Evaluation of Models

Tables 2 and 3 represent the results of neural network and multivariate regression models on the prediction of energy demand. According to these tables, the neural network model has the best performance in predicting the energy demand of the agricultural sector in terms of all three criteria compared to multivariate regression method.

Table 2 – The actual and predicted values of energy consumption (the equivalent million barrels of crude oil) by different models

Year	Actual Values	REG	ANN
1	33.142	31.981	29.58
2	16.603	18.891	15.676
3	10.413	16.246	10.522
4	30.271	34.183	31.631
5	12.701	16.387	11.783
6	21.189	21.886	23.647
7	16.718	18	14.225

Table 3 – The performance of various models in prediction of energy consumption

	REG	ANN
RMSE	3.2	2.1
RSE	0.12	0.07
ME	6.37	3.01
R^2	0.937	0.942

6. Conclusion and Suggestions

In economic discussions, in addition to labor and capital factors, the energy is considered as one of the most important production factors, so that it plays a crucial role in the economic life of the countries along with other factors. The importance of energy in the manufacturing process of different products its rareness requires further attention of economic actors to make efficient use of this factor. The officials of those countries are trying to control the parameters of energy supply and demand efficiently by more accurate prediction of the energy consumption and proper planning to conduct the energy consumption.

In this study, the amount of energy consumption in the Iranian agricultural sector was predicted using neural network and multivariate regression models. The annual data on the energy consumption of the agricultural sector was used as the output of the predictive models. The annual data on the total population and agricultural products (including agriculture and animal husbandry products) was used as the input variables of the predictive models. The results showed that artificial neural networks had a better performance than regression equations in terms of all evaluation indices.

The results of the present study confirm the results of previous studies in the field of price prediction and consumption of energy carriers on the higher accuracy of neural network models than regression models including Naseri and Kouchakzadeh (2008), Abrishami et al (2010), Shakibae et al (2008), Azari et al (2008), Pourkazemi and Asadi (2009), Menhaj et al (2010), Sadeghi et al (2011), Dashti Rahmatabadi et al (2011) and Yu et al (2008). The present study evaluated the performance of the aforementioned models for prediction of energy demand in the agricultural sector of Iran. It is suggested that the future studies predict the energy consumption of other economic sectors and assess the performance of the proposed models. Also, by combining the neural networks and fuzzy sets, the accuracy of the combined model can be compared with the predictive models of the present study.

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