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An Estimation of Energy Consumption in Iran's Transportation Sector Using Artificial Neural Networks Compared to Multivariate Regression Method

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ABSTRACT

The increasing reliance of human life on energy has had this factor (energy) play a significant potential or actual role in the performance of different economic sectors in several countries. So, any country's authorities must try to control the parameters of energy supply and demand favorably through ever more precise estimation of energy consumption and accurate planning in directing it. The current research aimed to create models for and estimate the energy consumption of Iran's transportation sector using neural networks. So in this research, the annual energy consumption data of Iran's transportation sector was used as the output variable for estimation models and the annual data of the total population of Iran, GDP (Gross Domestic Production) and the number of vehicles as the input variables of the same models. In the end, the precision of estimations in the above-mentioned models was assessed using assessment indices. The results showed that compared to the multivariate regression model, the neural network model was more precise in estimating the energy consumption of Iran's transportation sector.
KEYWORDS: Energy consumption, Multivariate regression, Artificial neural networks, Iran.

1. INTRODUCTION

Energy has been considered as one of the important factors of production in the past decades. It has played a determinative role in the economic life of countries along with other production factors, and its importance has increasingly heightened with economic growth and development. The increasing reliance of human life on energy has had this factor (energy) play a significant potential or actual role in the performance of different economic sectors in several countries (Behboudi et al, 2009). Securing energy supply is one of the strategic issues states in the world have to face. Less concerned about compared to the management of energy supply is the management of energy demand. Attempts in Iran have been directed these days more toward the management of energy supply than the management of energy demand, while the latter and trying to make optimal use of energy have been one of the most important factors of stable industrial development in all the advanced countries in the world (Mobini, Dehkordi et al, 2009). Iran has rich and extensive energy resources, huge resources of oil and natural gas, huge underground mines, and high energy potential. Prediction of energy consumption can effectively help to Energy sector policy. Limiting energy consumption especially petroleum products such as gasoline is the head of the government's economic policies. On the other hand, gas pressure drop problems such as gas cut in different provinces or reduce power generation in some Factories, sometimes suffered our country. In addition, shortage of other energy resources sometimes becomes problematic for different economy sectors. For reasons mentioned above, prediction and modeling of power consumption can be a useful guideline for policy makers of energy sector and economy of country (Amadeh et al, 2009). Therefore, country's authorities must attempt to effectively control energy demand and supply parameters by more accurately prediction of the energy consumption and proper planning for the guidance consumer. Although statistical and econometric method has relatively good performance in time series prediction, but it has some limitations, including it is possible that in these methods, conditioned form of independent and dependent variables not specified correctly. Moreover, irrelevant data may lead to biased estimates of model parameters. On the other hand, most of the time series model are Linear and therefore are unable to explain the nonlinear behaviors (Abrishami et al, 2010).

Artificial intelligence models have been usually used as non-linear estimation tools that have the potential to resolve the above-mentioned problems (Javadpour and Kanap, 2003). The current research aimed to employ neural network models for the estimation of energy consumption in Iran's transportation sector so that in the end, the efficiency of this method in estimation of energy consumption could be assessed.

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2. RESEARCH LITERATURE

Creating models for energy consumption and demand are usually based on previous patterns of consumption and its relation to other variables such as economic, population, weather, and energy cost variables. Below, the researches done in the same field are briefly reviewed.

The domestic researches already done on the use of neural networks in estimations are as follows: The estimation of Iran's petroleum products consumption by Taghzian and Nasr Abadi (2006), the estimation of the monthly price of Iran's crude oil by Ahmadi Gharachi (2006), the estimation of the total consumption of oil and gas in Iran by Amin Naseri and Kouchak-zadeh (2008), the estimation of Iran's diesel price by Abrishami et al. (2008), the estimation of crude oil production in 11 oil-producing countries by Shakibaei et al. (2008), the short-term estimation of natural gas consumption in Tehran by Azari et al. (2008), the dynamic estimation of crude oil price in Iran by Pour-Kazemi and Asadi (2009), the estimation of the energy demand of Iran's transportation sector by Menhaj et al. (2010), the estimation of daily price of crude oil basket by Sadeghi et al. (2011), the estimation of Iran's crude oil price by Dashti et al. (2011), and the estimation of electricity consumption of Iran's agriculture sector by Ebrahimi (2012). The following are among the foreign researches done in the same field: the estimation of heat consumption in buildings and energy consumption in solar buildings by Calgira (2000), the estimation of gasoline consumption in Lebanon by Nasr et al. (2002), the estimation of energy consumption in Turkey's transportation sector by Murat and Silan (2005), the estimation of Taiwan's power consumption by Pao (2006), the estimation of petroleum products consumption in Turkey by Sazin et al. (2007), the estimation of energy vehicles' price by Yo et al. (2008), the estimation of South Korea's energy demand by Gim and Rouper (2009), the estimation of crude oil price by Koulkarni and Heydar (2009), the estimation of energy consumption in Greece by Ekonomo (2010), and the estimation of energy consumption in Turkey by Cancale et al. (2001).

As it could be seen in the above-mentioned researches, energy is so important a factor that numerous researches have been done on its consumption and price where each research had its own special method for estimation and study. Such researches could be divided into two groups: The researches carried out using econometric methods and those done using artificial intelligence and neural networks methods. In all the above-mentioned researches, the efficiency and higher precision of neural networks have been confirmed. In this research, attempts were also made to estimate the energy consumption of Iran's transportation sector using neural networks model and compare the results with the regression model.

3. MATERIALS AND METHODS

3.1. Artificial Neural Networks

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). Artificial neural networks are comprehensive and flexible functions and a strong tool to analyze data and create models of non-linear equations with a high degree of accuracy. One of the mostly used neural networks is the Multilayer Perceptron Neural Network. A multilayer perceptron is a standard combination of inputs, linear and non-linear neural units, and outputs. The outputs of all processing units in each layer are transferred to the processing units of the next layer in this model. The processing units of the input layer are all linear, but in the hidden layers of neurons, hyperbolic, tangent sigmoid, or any other non-linear continuous differentiable function could be used. The outer layer neurons are usually chosen as to be linear in order to speed up the learning process. The major issue in such networks is how to determine the number of hidden layers and their neurons, and there are different opinions about this. The hidden layer is of high importance in neural networks models. Enough of these layers and units in a neural networks model plays an effective role in the learning process. Such layers are solely an intermediate result of output values calculation process, therefore, there is no counterpart for them in econometrics. The number of hidden nodes is important because they play a significant role in the non-linear configuration of neural networks (Zung, 2003). The input layer, similar to the five senses in relation with brain, receives inputs from outside the system (model). Trial and error method are mostly used to determine the number of input nodes; however, in general, the number of neurons in the input layer reflects the number of input variables (Malik and Naserdin, 2006). Concerning this, Nilsson (1987) proved that in neural networks with a hidden layer of sigmoid function $f(x) = \frac{1}{1+e^{x}}$ in the intermediate layer and a linear function in the output layer could approximate all the functions with any degree of approximation, in case there are enough neurons in the hidden layer. This theorem is known as the Universal Approximator (Menhaj, 2005). Fig. 1 shows the MLP network that is used in this study (Madahi & Salah, 2012):

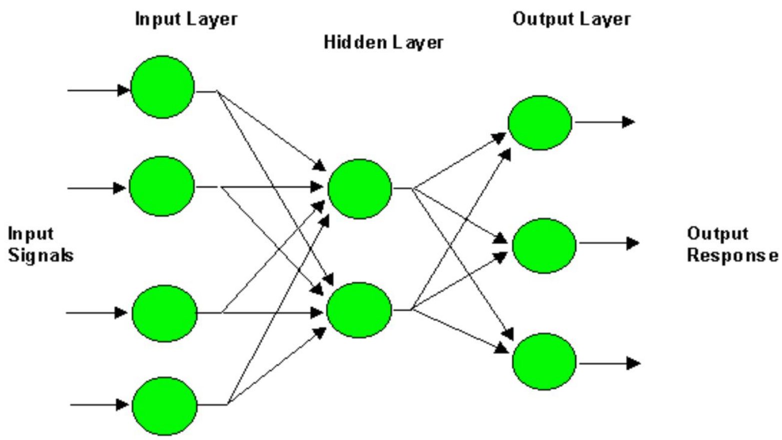

Figure1. Artificial Neural Network

3.2. Models Assessment Indices

Since there is no general consensus concerning the best performance criteria in assessing estimation models, the results of models' estimations are measured using several performance indices (Zung and Hio, 1998). In order to assess the performance of fuzzy, genetic, and artificial neural networks in this research, Relative Standard Error (RSE), Mean Error (ME), Root Mean Square Error (RMSE) were used and calculated using the following equations (Sarmadian et al, 2010).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Z_0 - Z_p)^2} \quad (1)$$

$$RSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Z_o - Z_p)^2}}{Z_{ave}} \quad (2)$$

$$ME = \frac{1}{n}\sum (Z_o - Z_p) \quad (3)$$

$$RI = (\frac{RMSE_a - RMSE_b}{RMSE_a}) \times 100 \quad (4)$$

Where, Z_0: Estimated amounts, Z_p: Observed amounts, Z_{ave}: Observed amounts average, n: the number of data

3.3. The Characteristics of Input and Output Parameters

Since artificial neural networks are based on data, preparing the data is an important step and, in fact, the key to the successful application of neural networks. The more the number of data, the more reliable is the approximation of hidden structures in the model. In this research, the annual data of energy consumption, including power, natural gas, and petroleum products, in Iran's transportation sector were used as the output variable of estimation models, and the annual data of Iran's total population, GDP, and the number of vehicles in the country as the models' input data. The interval for these variables was 1968 to 2005. It should be noted that the annual data of these variables were collected from the statistical sections of Iran's Ministry of Energy and Ministry of Industries and Mines (Menhaj et al, 2010). Data analysis was done using Minitab and Neuro Solution software. The current research had several stages; in the first stage, data was divided into 2 groups of test data and data for the purpose of learning; then, neural network algorithm was used to estimate the energy consumption; finally the results from several algorithms were assessed using model assessment indices, and the appropriate and efficient model for the estimation of energy consumption in Iran's transportation sector was determined. The research process is summarized in the following figure.

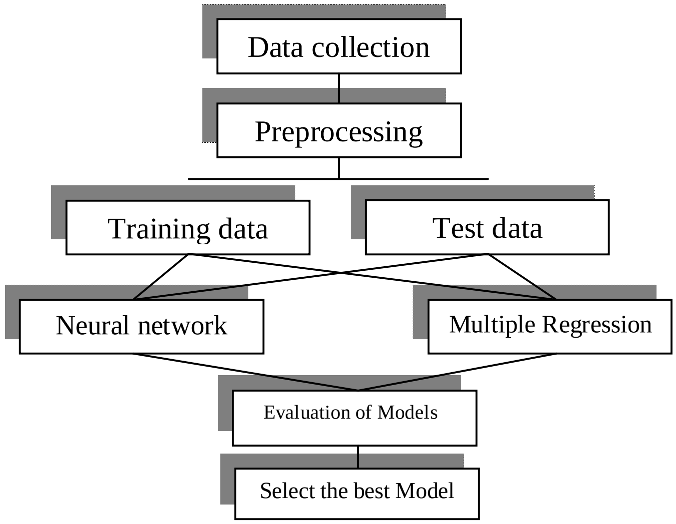

Figure 2: The research process

4. RESULTS

4.1. The Results of Linear Multivariate Regression

In this research, first, data was divided into 2 groups: 80% of it was dedicated to learning and the rest 20% to validation. To do this, the 2 groups were chosen randomly. In order to determine the multivariate regression of the parameters under study, the respective regression equation was determined using the data for learning (Equation No.5). The equation was then applied to the test data and the amounts of Root Square Error, Relative Standard Error, Mean Error, and the Coefficient of Determination were 6.09, 0.05, 5.11, and 0.993, respectively. P was assumed to be less than 0.01 in regression coefficients. Also, variance analysis table was calculated for the regression, and the results suggested that the attained fitting equation was significant (P<0.01). So, Assumption of linearity between two variables is confirmed and shows that regression model is able to explain changes in the dependent variable (Table 1).

$$y = -0.0826 + 0.290\,X1 + 0.313\,X2 + 0.483\,X3 \quad (5)$$

In the above equation,
X1: The number of vehicle, X2: Population, X3: GDP, Y: The ultimate consumption of energy in Iran's transportation sector

Table 1: The results of variance analysis for the regression

Source	Degree of freedom	Sum of squares	Mean square	F. Fisher	P Value
Regression	3	1.531	0.510	536.75	<0.01
Residual Error	27	0.025	0.00095		
Total	30	1.557			

4.2. The Results of the Neural Network

In designing a neural network model, the size of the test and learning groups, data normalization, the number of network hidden layers, the number of each layer's neurons, learning algorithms, transformation function, performance function, the rate of learning, and the number of repeats shall actually be determined. There are no systematic ways to do so, therefore, a network is best designed by the application of experience and trial and error. In this research, after the test and learning data were determined, the network input data was standardized using the equation 6. In case the network is fed with raw data, the high variance of such data affects the network in a different way so that some neurons will reach firing threshold very soon, while other neurons have not yet reached their activity threshold, and this decreases a model's estimation capability (Menhaj, 2005).

$$y = 0.8 \times \frac{X_i - X_{min}}{X_{max} - X_{min}} + 0.1 \quad (6)$$

X_{min} is the minimum data and X_{max} is the maximum data for the input data series in the above equation. Using this equation, input data will be between 0.1 and 0.9.

In this research, the network was designed so that it had a hidden layer with sigmoid activation function $f(x) = \frac{1}{1+e^{x}}$ and a linear activation function in the output layer. The number of neurons in this network could vary from 1 to 10, but their optimum number was determined using trial and error. Being efficient, simple and fast, the learning Levenberg-Marquardt Algorithm was used in this research. To estimate the energy consumption, the network inputs were chosen to be population, the number of vehicles, and GDP. For this feature, RMSE amounts are presented in figure 1 according to which the minimum amount of RMSE belongs to the hidden layer of a network with 9 neurons. As it's obvious in this figure, the variations of RMSE have no definite trend, because neural network is a black-box model and weights are chosen randomly, so, there is no thorough explanation for the trend just mentioned. The only way is to procure the best structure possible using trial and error. The best explanation for doing this is that as the model becomes more complex, the neural network inclines toward learning more than enough and could not properly fit itself to the new data.

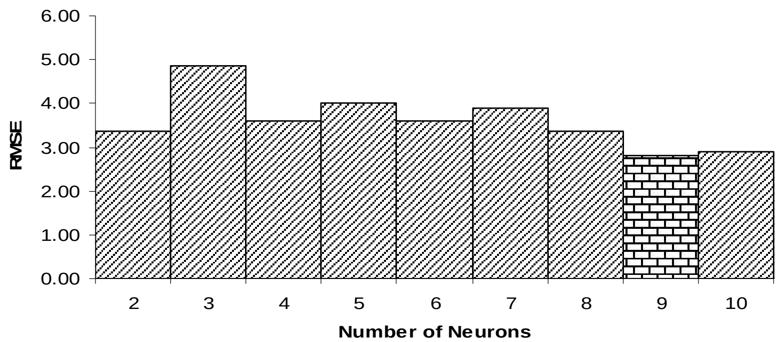

Figure 3: RMSE amounts for different numbers of neurons

4.3. A Summary of Results and the Assessment of Estimation Models

Results of using neural network models and multivariate regression method for the measured parameter are summarized in Table 2. According to this table, the best performance in estimating the feature under study belongs to neural network models that have performed better than multivariate regression concerning all 4 criteria.

Table 2: The actual and estimated rates of energy consumption and the performance of different models

Neural network	Regression	Actual values	Year
19.847	8.613	19.685	1971
57.128	57.164	53.755	1981
80.716	86.462	82.794	1986
82.801	88.274	86.557	1987
136.099	135.955	136.97	1995
163.509	157.236	161.195	1998
170.295	162.629	170.196	1999
226.039	212.321	220.823	2003
2.81	6.09	RMSE	Models Assessment Indices
0.021	0.05	RSE	
2.23	5.11	ME	

4.4. Sensitivity Analysis of Neural Networks

Sensitivity analysis is actually a method in which the rate of variation in output is analyzed by causing variations in inputs. This indicates that which input affects the output the most (Mirghafouri et al, 2011). In this research, sensitivity analysis of the neural network was used to determine which input variables namely the number of vehicles, population, and GDP had the biggest effect on the output – energy consumption rate. As it's obvious in figure 2, the parameters of population (X3), GDP (X2), and the number of vehicles (X1), had the biggest effect on the output (energy consumption rate) in the order just mentioned.

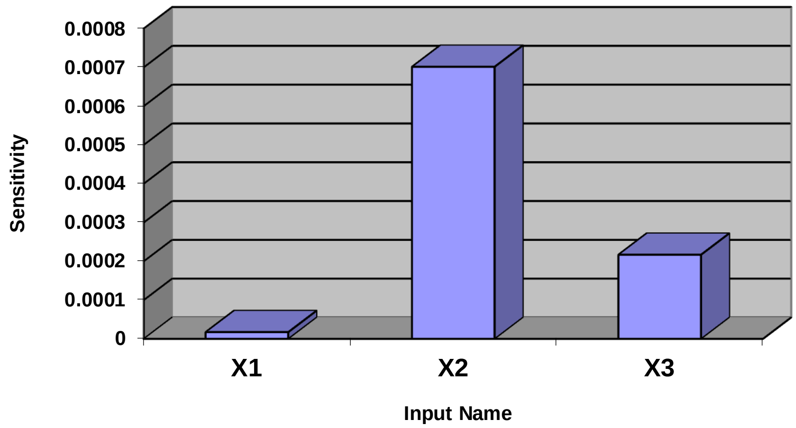

Figure 4: Sensitivity analysis of input parameters using the neural network

5. Conclusion and Suggestions

Energy is the vital and basic element of production that exists in different forms in nature, from wood and fossil fuels with the lowest level of refining to the nuclear energy with the highest level of processing. The increasing reliance of societies on energy because of the replacement of human workforce with machines has made energy be considered as an effective factor in economic growth and development and play a significant role in the performance of several economic sectors along with other factors of production. Therefore, the authorities in any society try to control the parameters of energy demand and supply by the ever more precise estimation of energy consumption in their societies and accurate planning to direct it. Using neural network and multivariate regression models, this research assessed the consumption of energy in Iran's transportation sector. In a similar study in the same field, the annual data of the energy consumption in Iran's transportation sector was used as the output variable of estimation models and the annual data of Iran's total population, GDP, and number of vehicles as the input variables of the same models (Menhaj et al, 2010). The research results showed that artificial neural networks were more efficient than regression equations concerning all the parameters of assessment. The results of former researches done on the estimation of price and consumption of energy vehicles such as those by Ahmadi Gharache (2005) to predict the monthly price of crude oil, Amin Naseri and Kouchakzadeh (2008) to predict the total gas consumption in Iran, Abrishami et al. (2008) to predict the price of gasoline in Iran, Shakibaei et al. (2008) to predict the crude oil production in eleven producing country, Azari et al. (2008) to short-term prediction of natural gas consumption in Tehran, Poorkazemi and Asadi (2009) to dynamic prediction of oil price in Iran, Menhaj et al. (2010) to predict the energy demand in Iran transport sector, Sadeghi et al. (2011) to predict daily crude oil basket price, Dashti Rahmat Abadi et al. (2011) to predict crude oil price in Iran, Ebrahimi (2012) to predict the electrical energy consumption in agricultural sector of Iran, Yo et al. (2008), etc. confirm the higher precision of neural networks models compared to regression ones. Also, the sensitivity analysis of input parameters using the neural network suggested that the input parameter of population has the biggest effect on the output – energy consumption. The current research studied the efficiency of the aforementioned models in the estimation of energy consumption in Iran's transportation sector. It is suggested that in the future researches, energy consumption in other economic sectors will be studied and the efficiency of the models mentioned earlier measured.

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