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Modeling and Predicting Agricultural Energy Consumption in Iran

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Abstract: According to economical theories and views, energy is one of the main and the most important production factors in agricultural section. Predicting its future consumption is an important step in macro-planning in agricultural and energy sections. To predict energy consumption in future in Iran agricultural section, time series models and artificial neural networks were used and the results were compared. To carry out the reviews, information of the time period of 1976-2001 was used for modeling and of 2002-2007 was used to compare the predictive power of these two mentioned methods. Results revealed that artificial neural networks had a better prediction in comparison with ARIMA model. Then, the annual energy consumption in agricultural section was predicted by neural networks for time period of 2008-2011.

Key words: ARIMA model % Artificial neural networks % Agricultural
JEL classification: B22 % C19 % C22

INTRODUCTION

Knowing the amounts of energy consumption is of great importance for two reasons. Firstly, in order for State policy makers and decision makers to make better economical decisions about proper and essential energy, they should know the way how the amounts of energy consumption are formed in different economical parts like the agricultural section. Therefore, every research carried out in a scientific framework to explain this subject is of importance. Secondly, in order to have planning in national level or even in an economical level, State economic authorities (including governmental and private) need to, predict factors affecting the price of merchandise and products of different sections in different time intervals , through an appropriate modeling.

Nowadays, nearly all nations and economical units have adjusted their policies not only an exclusively based status quo but also on short and long term predictions of economic key variables. In ARIMA method, predicting economical variables is done by themselves. In other words, since an economical variable includes all information related to it, it is considered the most robust source for explaining the changes of that variable. neural network models, which first were used by economists in 1990s, are one of the powerful tools for analyzing data in computer and engineering sciences and other scientific fields. In deed, artificial neural network models simulate the performance of the human brain using mathematical functions and processors. which they are able to model highly non-linear unknown relations. The main and the most important application of these models in economy is to perform modeling for predicting economical variables. Considering the importance of information about future events in this research after comparing predictive power of artificial neural networks and time series methods, the future of Iran´s energy consumption in the agricultural section was predicted for the years 2008-2011. Data required for this research for years 1976-2007 has been extracted from Iran Energy Balance Sheet.

Modeling electrical demand and energy consumption is usually based on historical consumption and the relationship of this consumption to other relevant variables, such as: economic, demographic, climatic, energy price, etc. Multivariate modeling along with cointegration techniques or regression analysis were used in a number of studies on different countries [1-7] to investigate the influence of different determinants on energy consumption.

Recently, some studies have analyzed forecasting performance for energy consumption using different models on different countries [8-10]. Darbellay and Slama [8] compared the predictions of nonlinear artificial neural networks (ANN) with linear ARIMA models for Czech electric consumption. They found that, for univariate modeling, the forecasting abilities of a linear model and a nonlinear model were not very different. For multivariate modeling, adding the temperature as an external input

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allows ANN to integrate more information and thus produce better forecasts. Saab *et al*. [9] investigated three univariate models, AR, ARIMA, and AR(1)/highpass filter, to forecast electrical energy consumption in Lebanon. They found that AR(1)/highpass filter model yielded the best forecast for this data set. Fatai *et al*. [10] used three econometric approaches to analyze the pattern of electricity consumption in New Zealand. They found that autoregressive distributed lag approach has the best forecasting performance. Variables affecting demand and energy consumption may vary from one region to another. A model developed for one region may not be appropriate for another region. Electrical consumption models are required for a variety of utility activities. Therefore, a model should be developed in different regions for efficient planning and organization.

Autoregressive Integrated Moving Average Modeling: The publication authored by Box and Jenkins ushered in a new generation of forecasting tools, technically known as the ARIMA methodology,10 which emphasizes on analyzing the probabilistic, or stochastic, properties of economic time series on their own rather than constructing single or simultaneous equation models. ARIMA models allow each variable to be explained by its own past, or lagged, values and stochastic error terms. If we have to difference a time series d times to make it stationary and apply the ARMA (p,q) model to it, we say the original time series is ARIMA(p,d,q). The importance point to note in ARIMA modeling is that we must have either a stationary time series or a time series that becomes stationary after one or more differencing to be able to use it. ARIMA methodology consists of four steps; namely, identification, estimation, diagnostic checking and, of course, forecasting.

Artificial Neural Network: In general, ANN are simply mathematical techniques designed to accomplish a variety of tasks. The research in the field has a history of many decades, but after a diminishing interest in the 1970s, a massive growth started in the early 1980s. Today, ANN can be configured in various arrangements to perform a range of tasks including pattern recognition, data mining, classification, forecasting and process modeling. ANN are composed of attributes that lead to perfect solutions in applications where we need to learn a linear or nonlinear mapping. Some of these attributes are: learning ability, generalization, parallel processing and error endurance. These attributes cause the ANN to solve complex problem methods precisely and flexibly. ANN consist of an inter-connection of a number of neurons. There are many varieties of connections under study, however, here, we will discuss only one type of network, which is called the multi-layer perceptron (MLP). In this network, the data flows forward to the output continuously without any feedback. Fig. 1 shows a typical three layer feed forward model used for forecasting purposes. The input nodes are the previous lagged observations, while the output provides the forecast of the future value. Hidden nodes with appropriate nonlinear transfer functions are used to process the information received by the input nodes. The model can be written as:

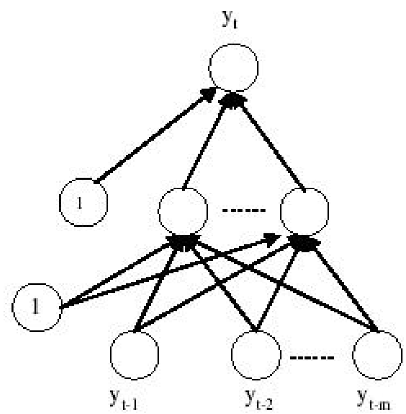

Fig. 1: A three layer MLP network

$$y_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j f\Big(\sum_{i=1}^{m} \beta_{ij} y_{t-i} + \beta_{0j}\Big) + \varepsilon_t \quad (1)$$

where, m is the number of input nodes, n is the number of hidden nodes, f is a sigmoid transfer function, such as the logistic function: $f(x) = \frac{1}{1+\exp(-x)}$. $\{\$_{ij}=0,1,..,n\}$ is a vector of weights from the hidden to the output nodes and $\{"_{ij}, i = 1, 2, \ldots, m; j = 0, 1, \ldots, n\}$ are weights from the input to the hidden nodes $\$_0$ and $"_{oj}$ are the weights of arcs leading from the bias terms, which have values always equal to 1. Note that Eq. (1) indicates a linear transfer function employed for the output node as desired for forecasting problems. The MLP's most popular learning rule is the error back propagation algorithm. Back propagation learning is a kind of supervised learning introduced by Werbos [11] and later developed by Rumelhart and McClelland [12]. At the beginning of the learning stage, all weights in the network are initialized to small random values. The algorithm uses a learning set, which consists of input-desired output pattern pairs. Each input-output pair is obtained by o. line processing of historical data. These pairs are used to adjust the weights in the network to minimize the sum squared error (SSE), which measures the difference between the real and the desired values over all output neurons and all learning patterns. After computing SSE, the back propagation step computes the corrections to be applied to the weights. ANN models have been researched in connection with many power system applications, short term forecasting being one of the most typical areas. Most of the suggested models use MLP networks [13-18]. The attraction of MLP networks has been explained by the ability of the network to learn complex relationships between input and output patterns, which would be difficult to model with conventional algorithmic methods. There are three steps in solving an ANN problem, (1) training, (2) generalization and (3) implementation. Training is a process by which the network learns to recognize the present pattern from the input data set. We present the network with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units. For this reason, each ANN uses a set of training rules that de.ne its training method. Generalization or testing evaluates the network's ability to extract a feasible solution when the inputs are previously unknown to the network and have not been used to train the network. We determine how closely the actual output of the network matches the desired output in new situations. In the learning process, the values of the inter-connection weights are adjusted so that the network produces a better approximation of the desired output. ANN learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully, otherwise useful time is wasted or, even worse, the network might be functioning incorrectly. The disadvantage is that because the network finds how to solve the problem by itself, its operation can be unpredictable. In this study, made to identify the best suited network for the desired model according to the characteristics of the problem and the ANN features.

Forecasting Evaluation Methods: For the purpose of evaluating out-of-sample forecasting capability, we examine forecast accuracy by calculating three different evaluation statistics, which are the root mean square error (RMSE), the Mean Absolute Deviation (MAD), and the mean absolute percentage error (MAPE). Their definitions are in the following:

$$MAD = \frac{\sum \left| (\hat{y}_t - y_t) \right|}{n}$$

$$RMSE = \sqrt{\frac{\sum (\hat{y}_t - y_t)^2}{n}}$$

$$MAPE = \frac{\sum \left| \frac{\hat{y}t - y_t}{y_t} \right|}{n}$$

where $\hat{y}_t$ and y_t are predicted and actual value, and *n* is the total number of predictions.

OBTAINED RESULTS

In this research, to predict the amounts of energy consumption in agricultural section, ARIMA models and multi-layer Perspetron (MLP) neural networks have been used. In both models, to simulate models and training, data of period 1976-2007 was used and to evaluate the predictive power of the mentioned models, four pieces of data related to years 2008-2011 were used.

Time Series Modeling

Artificial Neural Network: In this study, MLP neural network was used. the aim of this study is to compare the time series and artificial neural network models. number of neurons of the entrance layer the numbers of self-regression sentences in ARIMA model were determined in the given neural networked. Therefore, there are two neural in the entrance layer. MLP neural network has 8 neurons and a logistic activating function which in its exit layer and hidden layer have one neutron and a linear activating function with regards to the outputs of the network.

Comparing the Predictive Power: After estimating the models, to compare the predictive power of ARIMA (2,1,2) Model and Artificial neural Networks, MAPE, RMSE and MED criteria were used and the results are shown in Table 1. These criteria have been obtained based on the comparison of actual data of 2002-2007 and the predicted amounts.

According to the results of Table 1, all criteria show the preference of MLP neural networks over ARIMA

Table 1: Comparing forecasting measurement errors

	RMSE	MAD	MADP
ARIMA(2,1,2)	0.591	0.466	0.019
ANN	0.237	0.194	0.008

Table 2: Predicted amounts of annual energy consumption in the agricultural section

Year	2008	2009	2010	2011
Energy consumption forecasting(million barrel equal raw oil)	24.25223	24.40454	25.33481	26.2192

Model. According to the results, MLP model has the least error and subsequently the most efficiency in predicting annual energy consumption in Iran agricultural section. Then, the amount of annual energy consumption was predicted for years 2008-2011 using received neural network and the results are shown in Table 2.

To have a better understanding, actual and predicted amounts of annual energy consumption in the agricultural section are shown in Table 2.

Reviewing the above table reveals that over the past years the amount of energy consumed in Iran agricultural section had an increasing trend and prediction carried out for years 2008-2011 shows that this trend will continue.

CONCLUSIONS

In this study, modeling and predicting the amounts of annual energy consumption in agricultural section was performed using multi-layer Perspetron neural network model and ARIMA process. The amounts of annual energy consumption in agricultural section were used for modeling. The amounts related to years 1976-2001 were used for modeling and the amounts of 2002-2007 were used for intra-sample prediction and for comparing the predictive power of both models. Results revealed that artificial neural networks had a better prediction in comparison with ARIMA Model. Then, the amounts of annual energy consumption in agricultural section for years 2008-2011 were predicted using neural networks.

This prediction shows that energy consumption in Iran agricultural section will have an increasing trend as before and it warns the authorities that in a case the price of energy increases in Iran, the prices will have a huge increase in agricultural section and this has a negative effect on State competitive power.

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