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Using Different Method for petroleum Consumption Forecasting, Case Study: Tehran

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Abstract

Purpose: Forecasting of petroleum consumption is useful in planning and management of petroleum production and control of air pollution.
Research Design, Data and Methodology: ARMA models, sometimes called Box–Jenkins models after the iterative Box–Jenkins methodology usually used to estimate them, are typically applied to auto correlated time series data.
Results: Petroleum consumption modeling plays a role key in big urban air pollution planning and management. In this study three models as, MLFF, MLFF with GARCH (1,1) and ARMA(1,1), have been investigated to model the petroleum consumption forecasts. Certain standard statistical parameters were used to evaluate the performance of the models developed in this study. Based upon the results obtained in this study and the consequent comparative analysis, it has been found that the MLFF with GARCH (1,1) have better forecasting results..
Conclusions: Survey of data reveals that deposit of government policies in recent yeas, petroleum consumption rises in Tehran and unfortunately more petroleum use causes to air pollution and bad environmental problems.

Keywords: Petroleum Consumption; Forecasting; Multi Layered Feed Forward (MLFF); Air Pollution; Autoregressive–Moving-Average (ARMA) Models.

JEL classifications : O28.

1. Introduction

Petroleum consumption in Tehran city has raised remarkably in the past few decades due to the city's increasing population and economic development. Unfortunately Petroleum consumption causes to air pollution and many environmental problems. This has led to a need for better planning and design, and more efficient and management of Petroleum consumption.

Furtado and Suslick (1993) in their paper forecast petroleum consumption in Brazil for the year 2000 based upon logistic models, learning models, and Tran slog models using the technique of intensity of energy use. Models employ a time series of 30 years for projection. An investigation of the evolution of petroleum consumption profile was made based upon three characteristic effects: structural, content and scale effects. Evaluation of forecasting models presented good results, with the Tran slog model showing the best performance in terms of accuracy.

Loq (2011) in his paper investigates the effectiveness of the four parameter logistic model, the Gompertz Laird model and the stochastic Gompertz innovation diffusion model for describing the evolution of petroleum consumption in China. The three sigmoidal growth models are applied to the historical data on petroleum consumption in China. The developed models are compared using the goodness of fit to the historical data. The selected statistical measures are the coefficient of determination R^2, the mean squared error, the mean absolute percentage error, the mean absolute deviation and the Durbin Watson statistic d. The good model fit has indicated that the four parameter logistic model is a very appropriate candidate in forecasting petroleum consumption in China. Sadorsky (2006) uses several different univariate and multivariate statistical models to estimate forecasts of daily volatility in petroleum futures price returns. The out-of-sample forecasts are evaluated using forecast accuracy tests and market timing tests. The TGARCH model fits well for heating oil and natural gas volatility and the GARCH model fits well for crude oil and unleaded gasoline volatility. Simple moving average models seem to fit well in some cases provided the correct order is chosen. Despite the increased complexity, models like state space, vector autoregression and bivariate GARCH do not perform as well as the single equation GARCH model. Most models out perform a random walk and there is evidence of market timing. Parametric and non-parametric value at risk measures are calculated and compared.

Rao and Parikh (1996) analyses the demand for petroleum products in India. For this purpose, econometric models based on time series data are generated for individual products so as to capture product specific factors affecting demand. The models generated follow the non-homothetic Tran slog functional form. The models are validated against historical data by testing them for **ex post** forecast accuracy. Demand forecasts till the year 2010 are obtained for the various petroleum products using these models. The forecasts indicate a high rate of growth in demand for motor gasoline, high speed diesel oil, kerosene, and liquid petroleum gas and aviation turbine fuel. However, the demand for fuel oils, light diesel oil, naphtha and lube oils is expected to grow at a relatively lower rate.

The remainder of this paper is structured as follows. Section 2 describes the non-parametric modeling approach adopted here as per MLFF neural network and autoregressive–moving-average (ARMA) models, which are briefly discussed. Section 3 describes the model data. Empirical results are presented in Section 4, and concluding remarks in Section 5.

2. Artificial Neural Network

Artificial Neural Network (ANN) is biologically inspired network based on the organization of neurons and decision making process in the human brain. In other words, it is the mathematical analogue of the human nervous system. This can be used for prediction, pattern recognition and pattern classification purposes. It has been proved by several authors that ANN can be of great used when the associated system is so complex that the underline processes or relationship are not completely understandable or display chaotic properties. Development of ANN model for any system involves three important issues: (i) topology of the network, (ii) a proper training algorithm and (iii) transfer function. Basically an ANN involves an input layer and an output layer connected through one or more hidden layers. The network learns by adjusting the inter connections between the layers. When the learning or training procedure is completed, a suitable output is produced at the output layer. The learning procedure may be supervised or unsupervised. In prediction problem supervised learning is adopted where a desired output is assigned to network before hand. Based on research aim, varieties of artificial neural networks are used.

2.1. MLFF Neural Network

MLFF neural network is one the famous and it is used at more than 50 percent of researches that are doing in financial and economy field recently. This class of networks consists of multiple layers of computational units, usually interconnected in a feed-forward way. Each neuron in one layer has directed connections to the neurons of the subsequent layer. In many applications the units of these networks apply a sigmoid function as a transfer function ($f(x) = \frac{1}{1+e^{-x}}$). It has a continuous derivative, which allows it to be used in back-propagation. This function is also preferred because its derivative is easily calculated: $y' = y(1-y)$

Multi-layer networks use a variety of learning techniques; the most popular is back-propagation algorithm (BPA). The BPA is a supervised learning algorithm that aims at reducing overall system error to a minimum. This algorithm has made multilayer neural networks suitable for various prediction problems. In this learning procedure, an initial weight vectors w_0 is updated according to:

$$w_i(k+1) = w_i(k) + \mu(T_i - O_i)\, f'(w_i x_i)\, x_i \qquad (1)$$

Where, $w_i \Rightarrow$ the weight matrix associated with i[th] neuron; $x_i \Rightarrow$ Input of the i[th] neuron; $O_i \Rightarrow$ Actual output of the i[th] neuron; $T_i \Rightarrow$ Target output of the i[th] neuron, and μ is the learning rate parameter.

Here the output values (O_i) are compared with the correct answer to compute the value of some predefined error-function. The neural network is learned with the weight update equation (1) to minimize the mean squared error given by:

$$E = \frac{1}{2}(T_i - O_i)^2 = \frac{1}{2}[T_i - f(w_i x_i)]^2 \qquad (2)$$

By various techniques the error is then fed back through the network. Using this information, the algorithm adjusts the weights of each connection in order to reduce the value of the error function by some small amount. After repeating this process for a sufficiently large number of training cycles the network will usually converge to some state where the error of the calculations is small. In this case one says that the network has learned a certain target function. To adjust weights properly one applies a general method for non-linear optimization that is called gradient descent. For this, the derivative of the error function with respect to the network weights is calculated and the weights are then changed such that the error decreases.

The gradient descent back-propagation learning algorithm is based on minimizing the mean square error. An alternate approach to gradient descent is the exponentiated gradient descent algorithm which minimizes the relative entropy.

2-2 Autoregressive–Moving-Average (ARMA) Models

ARMA models, sometimes called Box–Jenkins models after the iterative Box–Jenkins methodology usually used to estimate them, are typically applied to auto correlated time series data.
Given a time series of data X_t, the ARMA model is a tool for understanding and, perhaps, predicting future values in this series. The model consists of two parts, an autoregressive (AR) part and a moving average (MA) part. The model is usually then referred to as the ARMA (*p*,*q*) model where *p* is the order of the autoregressive part and *q* is the order of the moving average part
The notation ARMA (*p*, *q*) refers to the model with *p* autoregressive terms and *q* moving-average terms. This model contains the AR (*p*) and MA(*q*) models,

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}. \qquad (3)$$

3. Model data

In order to estimate weekly petroleum consumption in Tehran, we introduce petroleum consumption in the previous 104 weeks as the input variables of the model. The petroleum consumption data were obtained from the Production and distribution of oil products Organization in Tehran. The petroleum consumption data for the most recent 104 weeks (2010-2011) were considered for model development and testing in this study.
For MLFF neural network all the data were divided into two sets, a training set consisting of first 70 weeks of data. The training data set was used to train, while the testing data set was used to test the performance of the model in term of various statistical measures. During the designing of MLFF model we have changed the number of layers and neurons. Finally we found the best network in this research as a network with 3 hidden layers and 20-15-10 neurons. Almost 100 transfer function has been used and sigmoid is used for the input function and the linear function is used for output.
For ARMA model we use from Box-Jenkins methodology for identification of AR and MA ranks. This method reveals that according to my data, I should use from ARMA (1,3) model for petroleum consumption forecasting.
In other method we use GARCH (1,1) for extracting volatility and import volatility as an input to MLFF model.

4. Empirical Result

RMSE and Dstat are used for comparison forecasting results of three models that I introduced in last section. The RMSE is calculated as: (Caslla and Lehmann)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{4}$$

Where e_i denotes the difference between forecasted and realized values and n is the number of evaluation periods. In the gas price forecasting, a change in trend is more important than precision level of goodness of fit from the viewpoint of practical applications. As a result, we introduce directional change statistics, Dstat. Its computational equation can be expressed as:

$$\text{Dstat} = \frac{1}{n}\sum_{i=1}^{n} |e_i| \tag{5}$$

Where $ei = 1$ if $(yi+1 - yi)(\hat{}yi+1 - yi) \geq 0$, and $ei = 0$ otherwise. (Wang et al) Forecasting results are shown in table1.

Table 1: Forecasting Results

Model	**RMSE**	**Dstat** (%)
MLFF	3.281	63
MLFF with GARCH (1,1)	2.943	72
ARMA (1,3)	3.293	61

It can be seen that the MLFF neural network model with GARCH (1,1) has lesser error than other models. Because of seasonal and monthly trend in water demand, it is difficult to forecast its trend by conventional methods such as regression and time series. Therefore, NN_s seems to be ideal for such unknown and fluctuating behavior.

5. Conclusion

Petroleum consumption modeling plays a role key in big urban air pollution planning and management. In this study three models as, MLFF, MLFF with GARCH (1,1) and ARMA(1,1), have been investigated to model the petroleum consumption forecasts. Certain standard statistical parameters were used to evaluate the performance of the models developed in this study. Based upon the results obtained in this study and the consequent comparative analysis, it has been found that the MLFF with GARCH (1,1) have better forecasting results..

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