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Predicting Electricity Consumption in Misan Province of Iraq Using Univariate Time Series Analysis

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Abstract
The goal of this research is to develop a suitable model for forecasting monthly electricity demand in Misan Iraq. Regarding the issue of electricity shortages and post-war industries rebuilding, this information is vital for Iraqi officials. Due to the lack of information on other variables those affecting power consumption, the focus of this research is on univariate models for short-term forecasting (up to two years). The data for this study are from January 2009 to June 2019. Several models were fitted to the data in three classes including exponential smoothing methods, Box-Jenkins models and state- space models. Different criteria were used to select the appropriate model. The randomness of the model residuals was investigated using Liang-Box criterion and the Akaike information benchmarks were calculated for each model. Also, a 12-month period was excluded from the latest data as the hold-out sample and used to test and validate the models predictions. The results show that Box-Jenkins modeling provides better results for these data. Finally, electricity consumption forecasts for a 24-month period in Iraq's Misan province are presented.

Keywords: Time Series Forecasting, Electricity Consumption, ETS Model, Box-Jenkins Models, State-Space Models.

Predicción del consumo de electricidad en la provincia de Misan, Iraq, mediante análisis de series de tiempo univariantes

Resumen

El objetivo de esta investigación es desarrollar un modelo adecuado para pronosticar la demanda mensual de electricidad en Misan, Iraq. Con respecto al tema de la escasez de electricidad y la reconstrucción de las industrias de posguerra, esta información es vital para los funcionarios iraquíes. Debido a la falta de información sobre otras variables que afectan el consumo de energía, el enfoque de esta investigación está en modelos univariados para pronósticos a corto plazo (hasta dos años). Los datos para este estudio son de enero de 2009 a junio de 2019. Se ajustaron varios modelos a los datos en tres clases, incluidos los métodos de suavizado exponencial, los modelos de Box-Jenkins y los modelos de espacio de estado. Se utilizaron diferentes criterios para seleccionar el modelo apropiado. La aleatoriedad de los residuos del modelo se investigó utilizando el criterio de Liang-Box y se calcularon los puntos de referencia de información de Akaike para cada modelo. Además, se excluyó un período de 12 meses de los últimos datos como muestra de reserva y se usó para probar y validar las predicciones de los modelos. Los resultados muestran que el modelado de Box-Jenkins proporciona mejores resultados para estos datos. Finalmente, se presentan pronósticos de consumo de electricidad para un período de 24 meses en la provincia iraquí de Misan.

Palabras clave: Predicción de series de tiempo, consumo de electricidad, modelo ETS, modelos Box-Jenkins, modelos espacio-estatales.

1. Introduction

Iraq is a major oil exporter that has just been through decades of war and crisis. By resolving ISIL danger and a relative political stability and relies on high oil revenues Iraq is taking steps to rebuild and expand. Under these circumstances, development of infrastructures such as energy supply, especially electricity, is a priority to meet current and future needs. The development of existing industrial and production units and the establishing of new ones also depend on the supply of electricity. It is becoming increasingly important to know that Iraq is currently struggling to provide electricity even to the citizens on hot summer days, and the lack of electricity has caused widespread discontent among the people, and even in some cases, it caused unrest. Iraqi officials are currently dependent on electricity supplies from neighboring countries, especially Iran. Therefore, analyzing existing data and creating a statistical model for predicting the future is of great importance. Such a model can help optimize the allocation of resources and make the right management decisions in the field of electricity. For example, licensing for start-ups will be very difficult without knowing the amount of electricity needed to start them. The purpose of this study is to analyze the electricity consumption data in Misan Iraq and to forecast the short-term (two-year) data using a statistical model.

In the current study, the only reliable data that we were able to obtain was regarding electricity consumption in Misan, Iraq, was monthly consumption during the period of January 2009 to June 2019. We, therefore, used univariate methods of forecasting for these data. In selecting the best model, we used accuracy measures such as MAPE (Mean Absolute Prediction Error), the goodness of fit criteria such as Akaike (AIC). We also used a 12-month period of the latest data as a holdout sample to test the accuracy of the predictions using Friedman and Wilcoxon signed-rank test. The results of our study showed that the SARIMA (0,1,1) (0,1,1)12 (Seasonal ARIMA) model for the logarithm of the data outperforms other models. Using this model, we provide monthly forecasts of electricity consumption for the next two years. The rest of the article is organized as follows. The Second section summarizes research on power consumption forecasts. In the third Section, the statistical models used in this study are briefly introduced. In the fourth Section of the paper, the results of the data analysis are presented and the models from three classes of time series including Box-Jenkins, exponentially smoothing and state-space compared. Section 5 of the paper, using the selected model the forecasting consumption for July 2019 to July 2021, provided and a brief discussion and conclusion are presented.

2. Literature review

Because of our complete dependence on electricity, it is important to predict the amount of consumption and demand for electricity. This means that authorities are always in need of accurate forecasts of electricity demand for the future. Saab, Badr et, al. (2001) predicted the monthly time series of power consumption using the ARIMA and AR (1) models with Highpass filtering, the results of which showed that the second model yields better predictions. Taylor, De Menezes et al. (2006) compared six time series

forecasting methods for one-day forecasting of electricity demand in Rio de Janeiro (hourly time series) and England and Wales (half-hourly time series). Their results showed that although exponential smoothing models were simpler than the other models used in the study, they performed better in prediction. Taylor (2010) has studied power generation data in the UK and France by extending the "triple seasonal methods" method. He showed that it performs better than double seasonal methods and univariate neural network approach. Also, Ediger and Akar(2007) and Zhu, Guo, et al. (2012) predict electricity demand and energy consumption in Turkey and China respectively using SARIMA, ARIMA and BVAR models, respectively. Other studies in this area include Huss (1985), Huss (1985), Price and Sharp (1986), Taylor (2003), Ramanathan, Engle, et al. (1997), Sharp and Price (1990), Abdel-Aal and Al-Garni (1997), Roken and Badri (2006) and Cho, Goude et al. (2013) have studied the demand analysis of electricity in different countries.
Many researchers consider the demand for electricity to be a function of other variables such as the number of subscribers, the number of hot days of the year, the cost of electricity bills, the variables related to economic growth, and so on (Roken and Badri 2006). However, the results of some researches such as Huss (1985b) show that for short- period time series, the predictions obtained from univariate time series models can be better than other more complex models. This result has been confirmed by some other researchers (see Roken and Badri 2006). Taylor, et al., (2006) have also advised using the univariate time series to predict short-periods. They have shown that simpler and more standard methods perform better than nonlinear and complex methods. The results of Taylor (2011) also showed that the exponential smoothing method performs better than the weather-based method.

3. Modeling methods used in the study

There are several ways to model and predict the time series. The three main classes of standard methods in this area are included exponential smoothing methods, Box-Jenkins models, and state-space models. Although there are numerous other approaches such as neural networks, fuzzy methods, principal component analysis or hybrid methods; many studies that investigate and compare the prediction methods indicate that the standard methods such as exponential smoothing and Box-Jenkins work well for predicting short-period time series (Taylor 2011; Taylor, et al. 2006). Of course, one cannot find a method that is clearly better than other methods (Piras and Buchenel 1999). In this study, due to the lack of access to environmental data affecting the electricity consumption and the results provided by other researchers that indicate the good performance of exponential smoothing methods, Box-Jenkins models, and state-space models, we have limited our research scope to these three classes.

3. 1 Box-Jenkins Models

Box-Jenkins modeling is actually a five-step algorithm. The first step is to stationary the data using variance stabilization transforms and differencing approach to achieve stationarity. The second step is model recognition using ACF and PACF plots. The third step involves fitting the ARIMA model or the SARIMA model. In the fourth step, the model is selected using criteria such as Akaike, and in the fifth step, the residuals of the model are tested using tests such as Ljung-Box to identify misspecification. If the model is inadequate, we have to return to step two and attempt to find a better model (Box, et al. 2015).

The time series $\{x_t\}_{t=1}^{n}$ follows an ARIMA(p,d,q) model whenever it has the following representation.

$$\phi_p(B)(1-B)^d x_t = \theta_q(B)a_t \tag{1}$$

where $\{a_t\}_{t=1}^{T}$ is white noise, B is the backward operator, and we assume that the autoregressive operator $\phi_p(B) = (1-\phi_1 B - \cdots - \phi_p B^p)$ and the moving average operator $\theta_q(B) = (1-\theta_1 B - \cdots - \theta_q B^q)$ does not have a common root and the roots of each of these polynomial lie outside the unit circle.

If the time series show a seasonal pattern with seasonal period s, then a multiplicative seasonal Box-Jenkins model which is represented as SARIMA(p,d,q)(P,D,Q)s can be used to model the data at hand as follows.

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D x_t = \theta_q(B)\Theta_Q(B)a_t \tag{2}$$

Where $\Phi_P(B^s) = 1-\Phi_1 B^s - \cdots - \Phi_P B^{Ps}$ and $\Theta_P(B^s) = 1-\Theta_1 B^s - \cdots - \Theta_P B^{Ps}$ are polynomials of B^s such that they don't have common roots and the roots of each lie outside the unit circle. A good source for studying the Box-Jenkins method is (Box, et al. 2015).

3. 2 State-space modeling

A state-space model in its general form contains a measurement equation and a state equation as follows

$$\begin{aligned} x_t &= D_t' s_t + \varepsilon_t, \\ s_t &= T_t s_{t-1} + R_t \eta_t, \ t = 1, \dots, n \end{aligned} \tag{4}$$

where x_t is the observation, ε_t is the observation error, and s_t is an invisible m×1 vector called the state vector. In model (3), D_t is a vector m×1 as the design vector, T_t is an m×m matrix as the transition matrix, and R_t is an m×r r≤m matrix as the selection matrix. Finally, η_t is also a vector ×1 of the state errors. r≤m means that all elements of the vector may not be stochastic. By properly defining the above vectors and matrices, various structural models including level, trend, seasonal component, intervention variables, and explanatory variables with stochastic or deterministic effects can be introduced. The class of state-space models is very broad, including even ARIMA models. Estimating the parameters and states (smoothing and filtering) and forecasting in state-space models are possible with the Kalman filter. A good source for further study of state-space models is Durbin and Koopman (2012).

3. 3 Exponential Smoothing Methods

Exponential smoothing methods include a range of simple but efficient methods for predicting univariate time series. The exponential smoothing method was established by researchers such as Brown (1959), Holt (1957), Winters (1960) and Pegels (1969). In general, all smoothing methods include a forecasting equation, in which level, trend and seasonal components integrated to make an h-step ahead prediction. The level, trend and seasonal components updated through differential equations (see Hyndman and Athanasopoulos (2018) for more details). In the equations, the combination of the component can be either additive or multiplicative. The trend can include a damped parameter (introduced by Gardner Jr and McKenzie (1985)) which flat the trend into a horizontal line at some future time. The damped parameter could be a multiplicative one (Taylor 2003a). Interest in inference problems such as making confidence interval for predictions motivated statisticians to find statistical models as the theoretical basis for exponential smoothing methods. There is some relation between some exponential smoothing methods and ARIMA models. For example, it is easy to show that the forecasts of simple exponential smoothing are equal to the forecasts of the model ARIMA (0,1,1). However, it is not possible to find an equivalent ARIMA model for all exponential smoothing methods.

Some statisticians used state-space modeling to formulate exponential smoothing methods (see for example Nerlove and Wage (1964), Theil and Wage (1964), Harrison (1967), Harvey (1984) and Chatfield (1996)). However, there were some problems in this regard, such that finding an appropriate state-space model for some exponential smoothing methods is difficult (Proietti 1998; Proietti 2000, Gardner Jr 2006). In the state-space model (4) let η_t=$\alpha\varepsilon_t$ then it becomes a single source of error (SSOE) state-space model which is introduced by Ord, et al. (1997) to model exponential smoothing methods. Using SSOE modeling enabled statisticians to easily model various exponential smoothing methods.

Hyndman and Khandakar (2007) and Hyndman and Athanasopoulos (2018) have introduced (Error, Trend, Seasonal) or ETS notation for SSOE models. Using this effective notation 30 different state-space models are possible for exponential smoothing methods. For the ease of readers, we repeat the following explanation from Hyndman and Athanasopoulos (2018). In an SSOE model, each of the three components (Error, Trend, Seasonal) could be either additive (A) or multiplicative (M). In addition, the trend component may include a damped parameter. In this case, we add the suffix "d". For example, the ETS model (A, Md, N) indicates a model with a multiplicative damped trend and additive error which does not include the seasonal component.

In many research articles the exponential smoothing method, especially with the damped trend, demonstrates its ability to provide accurate predictions (Fildes 2001, Fildes, et al. 2008 and Gardner and McKenzie 2011). Although the exponential smoothing method is a classical well-investigated method, it is still a field of study that has grabbed the attention of many researchers.

4. Modeling of electricity consumption data in the province Misan of Iraq

4.1. The data

The data of this study are the average monthly electricity consumption in the period from January 2009 to June 2019 in Misan, Iraq. Figure 1 shows the plot of time series of these observed data, along with the decomposing of this series into trend, seasonal, and random components. As it is obvious in the figure, from 2015 there exists an upward trend in the data and there is a clear 12-month seasonal cycle in the data. The plot also shows the instability in the mean and the variance of the time series. This evidence suggests a seasonal model and the use of appropriate transform to stabilize the variance.

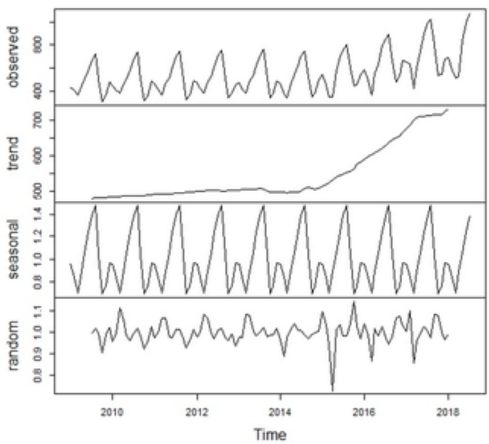

Fig. 1. Decomposing monthly electricity consumption into trend, seasonal and random components.

4. 2 The fitted models

In order to select the appropriate model, using the plot of time series data and its ACF and PACF plots, we candidate several models in each class. In order to stabilize the variance of the series we used a logarithmic transform. In selecting the appropriate model in the class of exponential smoothing methods and Box-Jenkins models, the automatic algorithm proposed by Hyndman and Khandakar (2007) which is available through r package forecast (Hyndman, et al. 2019) is very useful. In order to fit ARIMA and ETS models and estimating their parameters we used forecast package. For fit and test structural models in the state space class, we employed the r packages, KFAS (Helske and Helske 2019). After selecting the candidate models in each class, by performing the Ljuang-box test, the residuals of each model were evaluated for independence and constant mean and variance over time. Using the measure of accuracy MAPE and Akaike information criteria, the best model in each class was selected. The fitted models are as follows. The maximum likelihood method was used to estimate the parameters. The initial values are obtained by the initialization diffuse method.

Class 1: Seasonal Auto Regressive Integrated Moving Average

Model 1: SARIMA(0,1,1)(0,1,1)12

$$(1-B^{12})(1-B)\ln(x_t) = a_t - 0.7612a_{t-1} - 0.4861a_{t-12}$$

Class 2: Exponential Smoothing

Model 2: ETS(A,A,A) or Additive Holt-Winters Method

$$\ln(\hat{x}_{t+1|t}) = \ell_t + hb_t + s_{t-m+h_m^+}$$
$$\ell_t = \ell_{t-1} + b_{t-1} + 0.0329e_t$$
$$b_t = b_{t-1} + 0.00108e_t$$
$$s_t = s_{t-m} + 0.4369e_t.$$

where $e_t = \mathrm{Ln}(y_t) - \mathrm{Ln}(\hat{y}_{t|t-1})$ and initial states are:

l = 6.126

b = 0.0026

s = 0.0038 -0.2883 -0.3949 0.0983 0.4258 0.356 0.2236 0.099 -0.0708 -0.2564 -0.1539 -0.0421

Class 3: State Space

Model 3: The local linear trend model with a monthly stochastic seasonal dummy effect

Measurement equation $\ln(x_t) = z_t' s_t + \varepsilon_t,\quad \varepsilon_t \sim \mathrm{N}(0, \sigma_\varepsilon^2)$

State equation $s_{t+1} = T_t s_t + R_t \eta_t,\quad \eta_t \sim \mathrm{N}(0, Q_t)$

where

$s_t =$
$(6.592, 0.004, 0.367, 0.249, 0.091, -0.105, -0.321, -0.149, -0.022, -0.007, -0.248, -0.343, 0.067)'$
, $\eta_t = (\xi_t, \zeta_t, \omega_t)'$, $z_t = (1,1,1,0,\dots,0)'$,

$$T_t = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & -1 & -1 & 0 & \cdots & -1 \\ 0 & 0 & 1 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 1 & 0 & \ddots & 0 \\ \vdots & \vdots & \vdots & \ddots & \ddots & \cdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}, \quad Q_t = \begin{bmatrix} 3.69e-04 & 0 & 0 \\ 0 & 1.19e-10 & 0 \\ 0 & 0 & 3.64e-03 \end{bmatrix},$$

$$R_t = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \end{bmatrix}$$

Table 1 shows the evaluation results of the models in three classes. In terms of AIC information criteria and MAPE accuracy, the ARIMA model performs best for this data. Using Friedman test we compared the predictions of the three classes for a 12-month period with the hold-out data for the same period. Results indicated that ETS model predictions were significantly different (p-value <0.05). Table 1 shows the results of Wilcoxon sign-rank test for comparing the predictions of each method with the actual data. Model 2 predictions in the ETS class are significantly different from actual values.

Table 1. Assessment of the fitted models

Models	AIC	MAPE	Box-Ljung test (p-value)	Wilcoxon Signed Rank Test (p-value)
1	-244.38	0.627	0.4799	0.235
2	-49.04	0.682	0.0838	0.026
3	-174.33	0.576	0.0003	0.259

Figure 2 shows the time series plot of electricity consumption, along with forecasts of the three models for January 2018 to December 2019. As shown in the figure, the predictions of Model 1 are more proximate with the actual data than the predictions of the other two models.

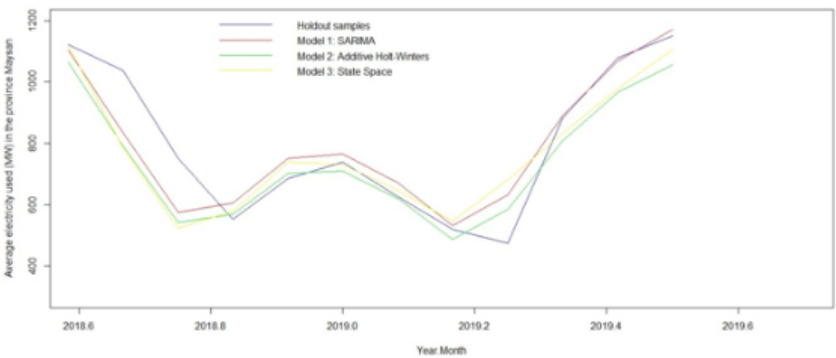

Fig 2. The plot of predictions for electricity consumption from three models (SARIMA, Additive Holt-Winters, and State Space) along with hold out data for the period January 2018 up to December 2019.

Figure 3 shows the time series of electricity consumption in Misan, Iraq, with forecasts from Models 1, 2 and 3 for August 2019 up to July 2021. The predictions of the SARIMA and ETS models are very close.

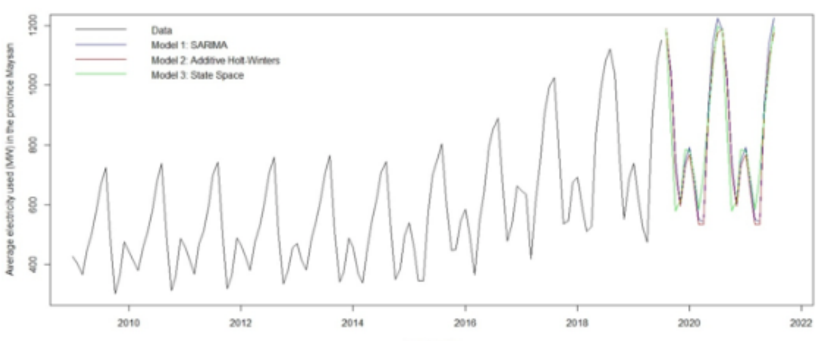

Fig. 3. Monthly electricity consumption (January 2009 up to July 2019) and the predictions of three models for the period August 2019 up to July 2021.

5. Discussion and Conclusion

In this paper, we analyzed the time series of monthly electricity consumption in Misan Iraq from 2009 to 2019. The data clearly showed a regular seasonal pattern and an increasing trend since 2015. For this time series, we fitted models in Box-Jenkins, exponential smoothing, and state-space classes. We used the last 12 observations as a hold-out sample to evaluate the models. We then compared the best models in each class using the AIC criterion, the MAPE accuracy measure, and the Wilcoxon sign-rank test. The performance of the state space class model was better than the exponential smoothing model. However, the residuals of the state-space model were not random. Model evaluation results showed that the SARIMA(0,1,1)(0,1,1)12 model is the most appropriate model for these data. Given the superiority of this model over other competing models, we have used it to predict monthly electricity consumption over the next two years. The predicted results are as follows

	Jan	Feb	Mar	Apr	May	Jun	Jul
2019							
2020	791.15	682.16	549.28	544.18	933.18	1139.59	1224.39
2021	847.69	731.34	590.79	601.85	998.75	1214.81	1310.33
	Aug	Sep	Oct	Nov	Dec		
2019	1181.28	1040.91	749.32	599.54	745.20		
2020	1260.09	1079.75	769.38	647.28	804.19		

Misan's average electricity consumption forecast for July 2021 is about 1310.33 MW, which is up 14% from July 2019 (1151 MW). Regarding this, the authorities should be prepared to supply this amount of energy from now on.

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