Time Series Analysis of Electricity Meter Supply in Ghana

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Abstract

Electricity demand is measured by the metered final consumption of end users.Therefore to supply power to consumers, electricity meter become a primary driver for measuring the amount of energy consumed by either industries, small and medium scale enterprises and homes.Due to the continuous demand for meters by client of the electricity company of Ghana and the company's inability to respond promptly with their demand there is therefore the need to model the supply of meters to estimate the monthly quantities needed to supply by the company to meet demand of their consumers. Little studies on meter supply and demand forecast have been carried out in order to develop the method to estimate the meter supply in Ghana. In this paper,Box Jenkins methodology is applied to total meter supply data from the Electricity Company of Ghana. On seasonal autoregressive integrated moving average ARIMA(1, 1,0) is tentatively used to model the data. Ljung-Box statistic is used in diagnostic checking and it is shown that the model is adequate.

Keywords: Meter supply, time series, Box-Jenkins method

Introduction

Electricity meter is a primary driver for measuring the amount of energy consumed by either industries, small and medium scale enterprises and homes. It is an integral part ofproduction and has effectively become 'essential' to the energymarket such that it cannot be under estimated. Virtually all forms of current industrial, manufacturing, and service activity require electricity to operate hence the need of meter to check their monthly consumptions and their associated cost. Although, some firms and individuals can and do function without it, it is impossible to compete meaningfully in today's global economy without access to cheap and reliable electric power. Hence the readily need for metering. The meters fall into two categories, electromechanical and electronic. But the next section will concentrate on prepayment metering

Prepayment Metering

Prepayment metering is a payment method where the consumer credits a special meter installed at the house, before the electricity is consumed. Prepayment metering is used by utility companies to provide service in instances where the consumer is considered a credit risk, or the consumer requests this method of payment (Speak, 2000). Payment meters can be used to collect payment of debt while continuing the supply of electricity (Electricity of Commission, 2007) and are often portrayed by retailers and are often portrayed by retailers and perceived by consumers as a useful budgeting tool (Boardman and Fawlett, 2002).

Coutard and Guy (2007) argue that the advantages of prepayment metering, and the appreciation that prepayment meter users have for them are often overlooked. Prepayment metering increases awareness of energy use, and a recent review of 12 pilot studies that investigate the effect of in home displays showing electricity use on consumer behavior found that the direct feedback provided encourages energy conservation (Faruqui *et al*., 2010).

Consumers who actively use in home displays reduce electricity consumption on average 7%, and when a prepayment meter is used in addition to an in home display consumption is reduced by about 14% (Faruqui *et al*., 2010). While reduced consumption may be beneficial from an environmental perspective, or in a purely economic sense, low income households tend to have less opportunities for reducing consumption and therefore less opportunities for reducing consumption (Colton, 2001). However, using prepayment metering provides greater budgetary control, and avoids the accrual of debt, in addition to disconnection and reconnection fees often applied to post-payment customer accounts where disconnection cannot be avoided. Prepayment metering may also empower low income consumers to choose when unavoidable disconnection may occur, and remove the need for embarrassing or stressful interactions with their electricity company about debt and disconnection (Coutard and Guy, 2007: Sharam, 2003).

Electricity and meter demand

Electricity demand is measured by the metered final consumption of end users.To supply power to consumers; however, generating plants also have to supply sufficient energy to compensate for the losses incurred in the process. Hence, any forecast of power needs must take account of losses that in some cases arehard to identify Chang *et al*(2002). In particular, losses in Ghana may arise not only from resistancelosses on the transmission and distribution wires, but also from theft of illegal connections which may normally arise as a result of meter shortage

A model with electricity demand as a function of household disposable income, population growth, the price of electricity and the degree of urbanization was reported by Hotedahl *et al* (2003) inTaiwan, They separated short and long-term effects through the use of error correction model. In their work they explained that energy demand model for a developing country may require a framework different from the use of industrialized countries.
One potential difference is that economic growth and structural changes associated with rapid development suggest that electricity meter supplies by the electricity company of Ghana will not be stable but may rise from months through years.

Due to the continuous demand for meters by client of the electricity company of Ghana and their inability to respond promptly with their demand there is therefore the need to model the supply of meters to estimate the month quantities needed to supply by the company to meet demand of their regional and district offices.

Electricity meters operate by continuously measuring the instantaneous voltage (volts) and current (amperes) and finding the product of these to give instantaneous electrical power (watts) which is then integrated against time to give energy used (joules, kilowatt-hours etc.). Meters for smaller services (such as small residential customers) can be connected directly in-line between source and customer. For larger loads, more than about 200 ampere of load, current transformers are used, so that the meter can be located other than in line with the service conductors. The meters fall into two categories, electromechanical and electronic.Jehl (1941)

Data

The data used throughout the study are the monthly meter supplied by the electricity company of Ghana. These data are supplied by the Management information systems department of the electricity company of Ghana. The data covered the period from January 2001 to December 2010. The measurements for 2004 were missing and the monthly average for the various years were used.

Methodology

Classical Box-Jenkins models describe stationary time series. Thus, in order to tentatively identify a Box-Jenkins model, we must first determine whether the time series we wish to analyze is stationary. If it is not, we must transform the time series into a series of stationary time series value. Differencing is often used to transform a nonstationary time series into a stationary time series. Stationary time series can be identified by examining the behavior of the sample autocorrelation function (SAC). In general, if the SAC of the time series value either cuts off or dies down fairly quickly, then the time series values should be considered stationary. Conversely, if the SAC of the time series values dies down extremely slowly, then the time series values should be considered nonstationary [2]. Once we have obtained a stationary time series value, we use the sample autocorrelation function (SAC) and sample partial autocorrelation function (SPAC) to identify a Box-Jenkins model describing the stationary time series value.

Two useful type of Box-Jenkins models are autoregressive models and moving average models.
The model $z_t = \delta - a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - ... - \theta_q a_{t-q}$ …….(1)

Is called the nonseasonal moving average model of order q .Here $a_t, a_{t-1}, a_{t-2}, ..., a_{t-q}$ are random shocks that are assumed to have randomly selected from a normal distribution that has mean zero and constant variance. Moreover the random shocks $a_1, a_2, a_3, ...$ are assumed to be statistically independence. $\theta_1, \theta_2, ..., \theta_q$ are unknown parameters that must be estimated from sample data. δ is a constant term and it can be proved that for the nonseasonal moving average model of order q , $\delta = \mu$

The model $z_t = \delta + \phi_1 z_{t-1} + \phi_2 z_{t-2} + ... + \phi_p z_{t-p} + a_t$ …(2)

is called the non-seasonal autoregressive model of order p where a_t is random shock and $\phi_1, \phi_2, ..., \phi_p$ are unknown parameters relating z_t to $z_{t-1}, z_{t-2}, ..., z_{t-p}$ and must be estimated from sample data. The prove exist for the fact that nonseasonal autoregressive model of order p ,the constant term $\delta = \mu\left(1 - \phi_1 - \phi_2, - ... - \phi_p\right)$.

Aside these two models, there is also a model that mix the models, called nonseasonal mixed autoregressive-moving average (ARMA) of order (pq)

$$z_t = \delta + \phi_1 z_{t-1} + \phi_2 z_{t-2} + ... + \phi_p z_{t-p} + a_t - a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - ... - \theta_q a_{t-q}$$

With $a_t, a_{t-1}, a_{t-2}, ..., a_{t-q}$ are random shocks,

$\phi_1, \phi_2, ..., \phi_p$ and are the autoregressive parameters and moving average parameters respectively.it can also be proved that for the ARMA model $\delta = \mu\left(1 - \phi_1 - \phi_2, - ... - \phi_p\right)$ Bowerman *et al*(2005)

SACF and SPACF Behavior

The behaviors of the SACF AND SPACF for each of the general nonseasonal models are presented in the table below.

Table 1.0 The behavior of SAC and SPAC for each of the general nonseasonal models.

Model	SACF	SPACF
$MA(q)$	Cut off after lag q	Dies down
$AR(p)$	Dies down	Cuts off after lag p
$ARMA(p,q)$	Dies down	Dies down

The point estimate of the Box-Jenkins models will be estimated as soon as data is analyzed with appropriate statistical software package. The parameter of the model were estimated using least square method.Importnance of each model parameter can be tested using the hypothesis that $H_o : \theta = 0$ against $H_a : \theta \neq 0$ .Using the t test we can reject the null hypothesis when the corresponding $p - value$ is the preset significance level α .the smaller the value of α at which $H_o : \theta = 0$ can be rejected ,the stronger the evidence that θ is important.Bowerman *et al*(2005), Cryer*et al* (2008)

Results and discussion

The time series analysis of meter supply data was conducted using R. First, we examine the stationary behavior of the monthly meter supply which leads to a single differencing to achieve stationarity. The behavior of SPACF and SACF for the time series was further examined.

Figure 1.0 and 2.0 present R output of the monthly total meter supply plot and the monthly differenced total meter supply plot of the data by the electricity company of Ghana. Figure 3 present R output of SPACF and SACF forthe monthly total meter supply data. We note that the SACF dies down afterlag1, while the SPACF dies down after lag 2 which indicate an ARIMA model with single differencing. Therefore, we can conclude that the data are stationary after the first differencingand we use the differenced data to continue the time series analysis

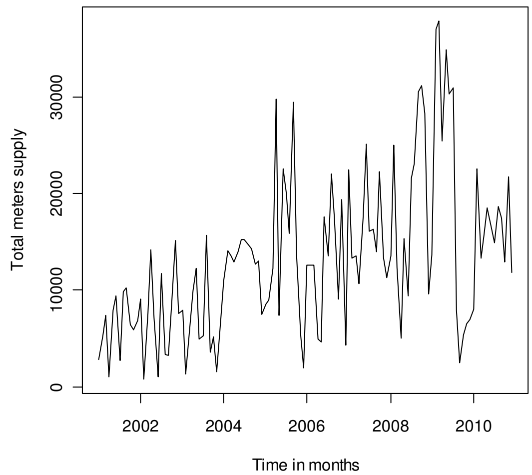

Fig 1.0 Monthly time series plots of total meter supply

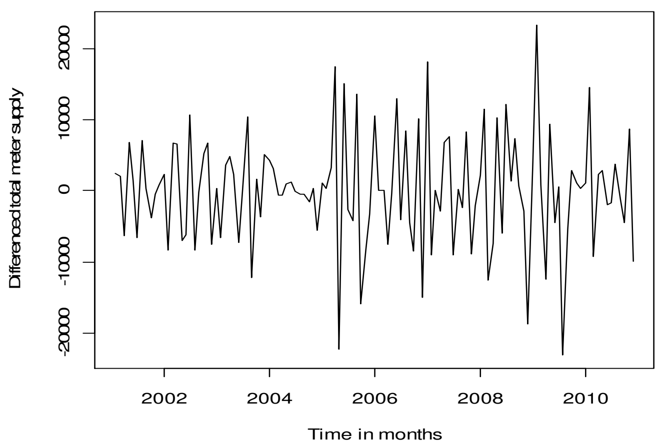

Fig 2.0 Time series plot for differenced total meter supply

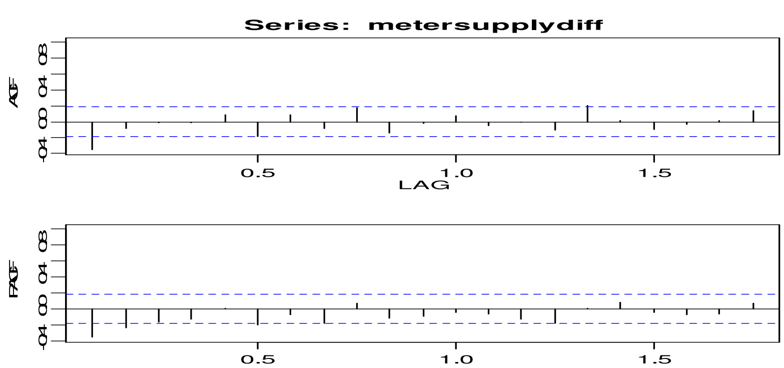

Fig 3.0 ACF and PACF plots for differenced total meter supply

Table 2: Best Model Identification

ARIMA(1,1,2)	AR	MA(1)	MA(2)	AIC	BIC
Coefficient	0.5439	-1.1359	0.1898	2445.01	2456.13
Standard error	0.2422	0.2747	0.2435		
ARIMA(0,1,2)					
Coefficient		-0.6030	-0.2446	2445.61	2453.95
Standard error		0.0861	0.0895		
ARIMA(0,1,1)					
Coefficient		-0.6525		2449.37	2454.93
Standard error		0.1123			
ARIMA(1,1,0)				2433.8	2452.14
Coefficient	-0.3568				
Standard error	0.0858				

Table 2 shows all the possible model for the total meter supply, the absolute of the quotient of the coefficient an it associated standard error were all found to be greater than two which indicate that all model specified are significant and can be used.

Since all identified model are significant, the following information criteria are used to check the model adequacy of a fit. In the case of the AIC, the model with the lowest AIC is the best model for use. Also for the BIC, the model with the lowest BIC is the best model for selection. However the BIC is biased towards the number of parameters used, it prefers models with a little number of parameters.

Comparing the AIC and BIC's of ARIMA(1,1,2), ARIMA(0,1,2),ARIMA(0,1,1) it is observed that ARIMA(1,1,0) has the lowest AIC And BIC values hence it is a preferable model compared to the rest.

Model Diagnostics

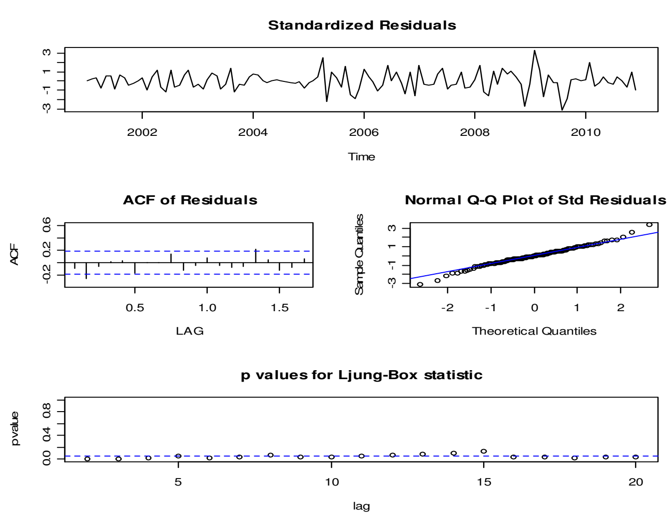

Figure 4.0

The first plot shows the standardized residual plot. By observation it is clear that the residuals are independent and identically distributed with mean zero.

The figure to the left to the Q-Q plot in figure 4.0 is the ACF plot of the residuals. If any of the positive lags should cut, then it can be said to have a significant correlation. Since two of the lags cut then, at least there is a significant correlation among some parameters.

The figure right to the ACF plot in figure 4.0 is the Q-Q plot which is used to check for normality. From above since most of the middle values lie on the straight line the dataset can be described as normally distributed.
The last plot in figure 4.0 is the Ljung-Box statistic. TheLjung-Box statisticis significant when all of the p-values lie below the line. Since the entire points lie below the zero line shows statistical significance and model adequacy.

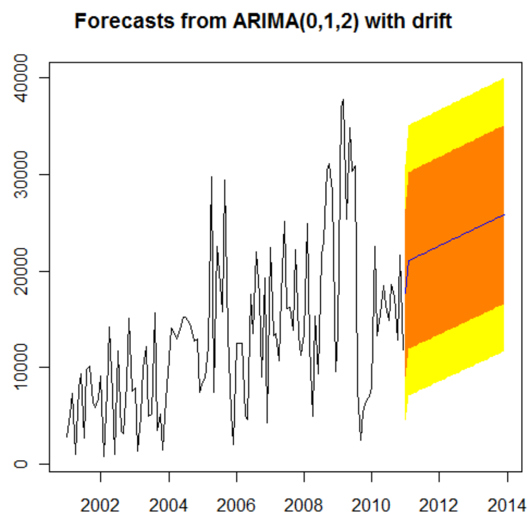

Figure 5.0 Prediction plot of monthly meter supply

Figure 5 shows the forecasting plot for the meter supply by the electricity company of Ghana. From the figure above, it can be deduced that meter supply will continually rise to be able to meet the demand of the customer. To be able to supply in order to meet the increasing demand of the customer the company will have to supply the upper confidence limit to be sure that the demand of the customers will meet their supply.

Conclusion

The demand for meters from the past trend and the model indicate an increasing trend. This presupposes that the demand for meters by the client will increase as the years increases. The model identified was very adequate to predict the supply of the meters by the electricity company of Ghana. The model will inform the company how many of the meters will they need to supply based on the demand of the customers. The management when taken of the model will inform them about .The meter supply data from Electricity Company of Ghana are analyzed using Box-Jenkins approach. Since the data was not stationary, differencing was applied to the data once to attain stationarity.Based on the behavior of SACF and SPACF, we tentatively identify the nonseasonal autoregressive of order 1, ARIMA (1, 1, 0). The test on the parameters of the model shows that all parameters are significant and important. The Ljung-Box statistics also indicate that the model is adequate. We confirm the conclusion that the model is adequate

References

Boardman, B., Fawcett, T., 2002. Competition for the poor. Liberalisation of electricity supply and fuel poverty: lessons from Great Britain for Northern Ireland. Lower Carbon Futures, Environmental Change Institute. University of Oxford, United Kingdom.

Bowerman, B.L, O'Connell, R.T, Koehler, A.B, 2005, Forecasting Time series and regression: An applied approach, 4th Ed., Belmont CA: Thomson learning.

Cryer, J.D, Chan, K-S (2008) Time series analysis with application in R, New York, USA, Springer.

Chang, Yoosoon and Martinez-Chombo, Eduardo, 2002. "Electricity Demand

Analysis Using Cointegrating and Error Correction Models with Time Varying Parameters: The Mexican Case," Working Paper. Department of Economics, Rice University.

Coutard, O., Guy, S., 2007. STS and the city: politics and practices of hope. Science Technology Human Values 32, 713–734.

Electricity Commission, 2007. Prepayment Meter Survey Results. Electricity Commission, Wellington.

Faruqui,A.,Sergici,S.,Sharif,A.,2010.Theimpactofinformationalfeedbackon energy consumption—a surveyoftheexperimentalevidence.Energy35, 1598–1608.

Holtedahl,P.,Joutz,F.L(2003).Residential electricity demand in Taiwan: Energy Economics,Vol.26,pp.201-224

Jehl, Francis (1941).Menlo Park Reminiscences.Kessinger Publishing.

Sharam, A., (2003). Second Class Customers: Pre-payment Meters, the Fuel Poor, and Discrimination. Energy Action Group, North Melbourne. Sherwood Burge, P., 2006. Prevention of exacerbations: how are we doing and can we do better? In: Proceedings of the American Thoracic Society, vol. 3, pp. 257–261.

Speak, S., (2000). Back to the well: the hidden costs of service exclusion for the network poor. Journal of Consumer Studies & Home Economics 24, 49–59.