Journal of Energy Technologies and Policy www.iiste.org
ISSN 2224-3232 (Paper) ISSN 2225-0573 (Online)
Vol.3, No.12, 2013

Modeling and Forecasting Energy Consumption in Ghana

Godfred Kwame Abledu(PhD)
School of Applied Science and Technology, Koforidua Polytechnic, PO Box 981, Koforidua, Ghana
E-mail of the corresponding author: godfredabledu@gmail.com

Abstract

Energy is a key infrastructural element for economic growth. It is a multitalented item that underpins a wide range of products and services that improve the quality of life, increase worker productivity and encourage entrepreneurial activity. This makes Energy consumption to be positively and highly correlated with real per capita GDP. In Ghana, between 2000 and 2008, while real per capita GDP growth averaged 5.5% per annum, annual Energy consumption growth averaged 1.21%. Inspite of the fact that real per capita GDP and Energy consumption are positively correlated, it is still not clear the direction of causality between real per capita GDP and Energy consumption.

These underscore the importance of and the need to develop modeling and forecasting tools as strategies for long-term planning. Herein lays the motivation for studying and modeling patterns of energy consumption the Ghanaian economy using seasonal ARIMA models. We obtained historical data of average monthly maximum energy consumption for the period 2001-2011 for the studies and those of 2009 for forecast validation of the chosen model, from the Ministry of energy. Model identification was by visual inspection of both the sample ACF and sample PACF to postulate many possible models and then use the model selection criterion of Residual Sum of Square RSS , Akaike's Information Criterion AIC complemented with the Schwartz's Bayesian Criterion SBC, to choose the best model. The chosen model is the SARIMA (1, 1, 1) (0, 1, 2) process which met the criterion of model parsimony with low AIC value of -845.79253 and SBC value of -812.34153. Model adequacy checks shows that the model is appropriate. The model was used to forecast energy consumption for 2013 and the forecast compared very well with the observed empirical data for 2012.

1.0. Introduction

Energy is a crucial input for production, manufacturing, and commercial activities. The importance of energy has increased in all fields as it is one of the fundamental inputs for economic development. On the other hand, energy consumption is permanently rising as the world population increases and technology advances. Therefore due to its leading role it in economic development and technological progress, the focus of the study is energy consumption. In 2008, the energy consumption of industrial sector accounted for 46% of total energy consumption, while services, agriculture, forestry and fishing sectors; households and transportation sector consumed 29%, 24% and less than 1% respectively. From 2000 to 2008 the energy consumption increased by 55%. Growth was slower for industrial sector (55%) and households (53%), but much faster at service sector (75%). Annual per citizen consumption is around 2.3 MWh that is one-quarter of International Energy Agency (IEA) average (IEA, 2009).

Energy consumption in Ghana is estimated to be increasing by 10% per annum due to the demand from the growing population. However, current sources of production (hydro and thermal facilities) generate only 66% of the current demand. Considering current trends, it is difficult to substantiate these basic facts, because of the lack of information. As a result, research into the existing sources of generating energy, energy consumption and prospective projects has been performed. This was achieved using three key techniques; review of literature, empirical studies and modelling. The results presented suggest that, current annual installed capacity of energy generation (i.e. 1960 MW) must be increased to 9,405.59 MW, assuming 85% plant availability. This is then capable to coop with the growing demand and it would give access to the entire population as well as support commercial and industrial activities for the growth of the economy. The prospect of performing this research is with the expectation to present an academic research agenda for further exploration into the subject area, without which the growth of the country would be stagnant.

Energy consumption in Ghana is estimated to be increasing by 10% per annum due to the demand from the growing population. However, current baseline production sources generate only 66% of the current demand. From this, an estimated 65% is used in the industrial and service sectors while the residential sector accounts for about 47% of total energy consumed in the country. Though this does not add up (certainly there must be justified reason), this is what has been presented in the Energy Sector Strategy and Development Plan, 2010 (www.ghanaoilwatch.org). This lack of parity prompts research to enable the validation of available data.

Reliable forecasting is an important part of planning and demand management of energy utilities (Harris & Lui, 1993). Residential Energy demand depends on a number of variables including weather, seasons, and technological factors to name a few (Stern, 1984). Utility forecasters are tasked with developing models that accurately predict demand. An extensive summary of energy modeling can be found in Hartman (1979) and Bunn and Farmer (1985).

Although there are a number of model types that can be used to investigate residential Energy demand, this study employs SARIMA model using basic input variables. Numerous researchers have published work ranging from selecting the appropriate method of forecasting (Chase, 1997) to how to use specific forecasting approaches in spreadsheets (Albright, Winston, & Zappe, 2005; Grossman, 1999; Kros, 2009; Ragsdale, 2006; Savage, 2003). Others have shown that the most commonly used method of forecasting is based on linear multiple regression (Brockwell and Davis, 1991).

Radovilsky and Eyck (2000) provided a much needed discussion on forecasting with Excel. Utility companies typically need forecasts that cover different time spans to achieve operational, tactical, and strategic intents. Utility firms know that seasonal variations impact demand, namely high and low energy consumptions and the four basic seasons. Technological advances and time also plays a role in demand as well as price. Technological advances combined with ''green'' initiatives on a consumer level such as solar water heaters, solar photovoltaic panels, and wind turbines directly impact residential demand.

Time plays a role in demand as residential housing square footage has increased and residential customers tend to use more Energy over time. Although price does impact residential energy demand, for the time frame of this study price has held approximately steady and will not be included in the model.

Utility companies typically need forecasts that cover different time spans to achieve operational, tactical, and strategic intents. Utility firms know that seasonal variations impact demand, namely high and low energy consumptions and the four basic seasons. Technological advances and time also plays a role in demand as well as price. Technological advances combined with ''green'' initiatives on a consumer level such as solar water heaters, solar photovoltaic panels, and wind turbines directly impact residential demand.

Time plays a role in demand as residential housing square footage has increased and residential customers tend to use more Energy over time. Although price does impact residential energyal demand, for the time frame of this study price has held approximately steady and will not be included in the model. Ragsdale (2006) argue that most of the literature on energy and economic development discusses how development affects energy use rather than vice versa. This strand of literature considers economic growth as the main driver for energy demand and only advanced economies with a high degree of innovation capacity can decrease energy consumption without reducing economic growth.

Bunn and Farmer (1985), on the other hand, have stressed the importance of considering the effect of changes in energy supply on economic growth in both developed and developing countries. If energy supply is considered a homogenous input for the production function, this means that if policy constraints affect energy supply, economic development is harmed. When energy services are differentiated, emphasizing the existence of higher and lower-quality forms of energy, society should make a choice in terms of an optimal energy mix, considering that higher quality energy services could produce increasing returns to scale. This means that energy regulation policies supporting the shift from lower-quality (typically less efficient and more polluting) to higher-quality energy services could provide impulse to economic growth rather than be detrimental. If we consider energy consumption as a function of economic output, regulation and technical innovation, a suitable representation is the formalization expressed in equation 1.

$$Y_{ij} = f\left(K_{ij.}L_{ij}, EC_{ij}\left(P_{ij}\right)\right) \tag{1}$$

where economic output (*Y*) is a function of the capital stock (*K*), labour (*L*) and energy inputs (*EC*), here modelled as being strictly dependent on energy prices (*p*). This simple assumption is required if we consider that energy supply is often affected by exogenous elements such as international energy prices and public regulation, assuming that public regulation can be fully expressed by domestic energy prices. We are aware that this is a simplification but we also know that, in many cases, energy taxes in OECD countries constitute the greatest part of energy prices.

These alternative views have important policy implications concerning, for example, aspects such as the development level of the considered country or the distributive effects related to the introduction of stringent energy (and environmental) regulations.

By observing energy trends in the past five decades, energy used per unit of economic output (energy intensity) seems to have steadily declined especially in advanced economies. The principal reason for this evidence is the shift in energy use from direct use of fossil fuels to the use of higher quality fuels (from coal to natural gas) or Energy.

If we consider highly industrialized countries, total energy use has increased, energy efficiency has improved and energy intensity - the energy necessary to produce output - has steadily fallen, especially in the industrial sector. Stabilization of greenhouse gas concentrations requires reductions in fossil fuel energy use which is a major essential input throughout all modern economies. If energy conservation and a switch from fossil fuels to alternative energy sources can be effected using new energy efficient technologies, the trade-off between energy and growth becomes less severe.

In order to obtain decoupled trends in the energy and economic sectors, an effort should be explicitly directed to possible win-win outcomes of energy (and environmental) regulation policies which are oriented towards technological innovation and productivity improvements. There are also changes in energy intensity that are not directly related to changes in the relative energy price but mainly explained by structural change in the productive composition (Stern, 1984). If the development process is in the deindustrialization phase, the increasing importance of value added produced by the service sector could lead to a global reduction in energy consumption due to a minor weight represented by energy-intensive industrial sectors.

The main focus of this work is to determine appropriate seasonal ARIMA model that can adequately predicts energy consumption in Ghana. The seasonal multiplicative ARIMA (Autoregressive, Integrated Moving Average) model is of the form

$$\phi(B)\Phi(B^s)Z_t = C + \theta(B)\Theta(B^s)a_t \qquad (2)$$

where $Z_t = \nabla^{d\nabla^D} \log y_t$, y_t is the observed energy consumption data at time t, $\nabla = 1 - B$ is the regular difference and $\nabla = 1 - B^s$ is the seasonal difference. D is the order of the seasonal difference while d is the order of regular difference. C is a constant and a_t is a white noise process. $\phi(B)$ is the regular autoregressive polynomial of order p while $\Phi(B^s)$ is the seasonal autoregressive polynomial of order P. Similarly, $\theta(B)$ is the regular moving average polynomial of order q while $\Theta(B^s)$ is the seasonal moving average polynomial of order Q. Sometimes, the model (2) is denoted SARIMA (p, d, q)(P, D, Q). The ARIMA model (2) is said to be invertible if all the roots of the moving average polynomial $\theta(B)\Theta(B^s)$ lie outside the unit circle.

Note that the model is already stationary. Many models can be formed from (2).These models are made of either past observed values together with a white noise or white noise only or a mixture of both. The major contribution of Box and Jenkins were to provide a general strategy in which three stages of model building were given prominence. These stages are those of model identification, estimation and diagnostic checks (Hipel et al. 1977 and McLeod, 1995).

2.0. Materials and Method

To test SARIMA models, historical data of average monthly maximum energy consumption for the period 2001-2011 was obtained from the Energy Commission in Ghana. Data for the first 72 months was used to fit the SARIMA models and the last 12 months as a hold-out period to evaluate forecasting performance and to monitor the energy consumption.

Before fitting a SARIMA model, the time series must be checked for violations of the weak stationarity assumption of the models (Brockwell and Davis, 2002). In SARIMA models, trend and seasonal nonstationarities are handled directly by the model Structure so that only the nonstationarity of variance needs to be addressed before model fitting.

The SARIMA models were fitted to the data using a semi-automated approach based on a combination of the Box-Jenkins method with small-sample, bias-corrected Akaike information criteria (AIC,) model selection (Brockwell and Davis, 2002). This approach involved three major steps: 1) selection of the candidate model set; 2) estimation of the model and determination of AIC,; and 3) a diagnostic check.

To detect possible presence of seasonality, trend, time varying variance and other nonlinear phenomena, the time plot of the observed data was inspected side by side with the plots of sample autocorrelation functions (ACF) and sample partial autocorrelation functions (PACF). This would help to determine possible order of differencing and and the necessity of logarithmic transform to stabilize variance. Non stationary behavior was indicated by the refusal of both the ACF values, ρ_n and the PACF, ϕ_{nn} to die out quickly. Also possible seasonal differencing was indicated by large ACF values, ρ_n at lags *s, 2s, ...,ns*. The technique was to apply both simple and seasonal differencing until the data was stationary. Stationary behavior was indicated by either a cut or exponential decay of ACF values ρ_n as well as PACF values ϕ_{nn}.

Model identification was by comparing the theoretical patterns of the ACF and PACF of the various ARIMA models with that of the sample ACF and PACF computed using empirical data. A suitable model was inferred by matching these patterns. Generally (Box and Jenkins, 1976), ARIMA (0, d, q) was indicated by spikes up to lag q and a cut to zero thereafter of the ACF values ρ_n complemented by an exponential decay or damped sine wave of the PACF values ϕ_{nn}.

ARIMA (p, d, 0) was identified by exponential decay or damped sine wave of the of the ACF values ρ_n complemented spikes up to lag p and a cut thereafter to zero of the PACF values ϕ_{nn}.When the process was an ARIMA(0, d, q)*(0, D, Q) then spikes would be noticed up to lag q + Qs. While ARIMA (p, d, 0)*(P, D, 0) was indicated by spikes at lag p+Ps and a cut to zero thereafter of the PACF.

Selection of the candidate model set was carried out by first analyzing sample estimates of the autocorrelation function (ACF) and partial autocorrelation function (PACF) in order to select the three major orders of the SARIMA models: d, D, and S. In this work, the model identification discussed above was used to give a rough guess of possible values p, q, P, and Q from which several models were postulated and then used the model selection criterion of Residual Sum of Square RSS (Box and Jenkins, 1976), Akaike's Information Criterion AIC (Akaike, 1974) to choose the best model. The AIC computation is based on the mathematical formula $AIC = -2\log L + 2m$, where $m = p + q + P + Q$ is the number of parameters in the model and L is the likelihood function. The best model was the one with the lowest AIC value. It was however noted that the likelihood was likely increased by addition of more parameters into the model. This would further reduce the value of the AIC leading to the choice of a model with many parameters. Brokwell and Davis (2002) emphasize on the need for the chosen model to meet criterion of model adequacy and parsimony. For this reason the RSS and AIC were complemented with the Schwartz's Bayesian Criterion SBC.

The SBC computation was based on the mathematical formula $SBC = -1\log L + mLogn$, where $m = p + q + P + Q$ is the number of parameters in the model and L is is the likelihood function. The SBC introduced a penalty function to check excess parameters in the model having identified a suitable SARIMA model, the next stage is the parameters estimation of the identified model and this is done through an exact maximum likelihood estimate due to Brockwell and Davis (2002). While forecast and prediction is by least squares forecast using a least square algorithm due to Brokwell and Davis (2002). When the estimated parameters are not significant, we do correlation analysis to remove redundant parameters.

The test for model adequacy stage requires residual analysis and this was done by inspecting the ACF of the residual obtained by fitting the identified model. If the model was adequate then residuals should be a white noise process. Under the assumption that the residual was a white noise process, the standard error of the autocorrelation functions should be approximately equal to $\frac{1}{\sqrt{n}}$ (Anderson, 1942. Hence under the noise assumption, 95% of the autocorrelation functions should fall within the range $\frac{\pm 1.96}{\sqrt{n}}$. If more than 5% fall outside this range, then the residual process was not white noise . the visual inspection of the residual ACF was complemented with the portmanteau test of Ljung and Box, 1978. This test provided a Q statistics defined by

$$Q = n(n+2)\sum_{k=1}^{m}(n-k)^{-1}r_k^2 \tag{3}$$

where r_k is the autocorrelation value of the residual at lag k, $n = N - d - D$. Q is approximately distributed as $\chi^2\left(m - p - q - P - Q\right)$. The technique here was to choose a level of significance and compare the computed Q with the tabulated χ^2 with $m - p - q - P - Q$ degree of freedom. If the model was inappropriate, the Q value would be inflated when compared with the tabulated χ^2.

Model estimation was carried out by using maximum likelihood methods, after conditional sum of squares estimation of the starting values (Brockwell and Davis, 2002). Diagnostic checks on the AIC-selected model involved the following steps: 1) verification of the resemblance of residuals to white noise (ACF plots, Ljung-Box test, cumulative periodogram test); 2) tests on the normality of residuals (Jarque-Bera and Shapiro-Wilks tests); and 3) confirmation of model stationarity, invertibility, and parameter redundancy (Ljung and Box, 1978). All tests were carried out at a significance level of a=0.05. The variance explained by the model was determined as $1 - \hat{\sigma}^2 / \sigma_{y_t}^2$.

3.0.Forecasts and model performance

The 12 months of model forecasts was evaluated, using the last month of the fitting data set as the forecast origin (2013). Forecasts were obtained in the mean- centered transformed scale ($\hat{y}_h, h = 1,...,12$) and in the original scale of the data ($\hat{x}_h, h = 1,...,12$), after correcting for back-transformation bias.

SARIMA model performance was assessed by comparing h-step forecasts ($\hat{x}_h$ and $\hat{y}_h$) with monthly energy consumption observed between 2011 and 2012(x_h and y_h). This was done by evaluating monthly forecast errors ($e_h = \hat{x}_h - x_h$) and then considering a set of accuracy measures: 1) annual root mean-square error (RMSE); 2) mean error (ME); 3) absolute percent error (APE_h); 4) mean absolute percent error (MAPE); and 5) annual Percent error (PE) . From these, RMSE was evaluated in the transformed scale to allow its comparison to 6, and all others were computed in the more user-friendly original scale of the data. Additionally, we compared the forecasting performance of the SARIMA model against two simple naive forecasting models (naïve model 1 or NM1, and naive model 2 or NM2.

To monitor the energy consumption we used two types of PI_s(Anderson, 1942): single step PI_s ($PI_{ss,h}$) and multistep PIs ($PI_{ms,h}$). Single step PI_s refer to a single monthly forecast (e.g., *h=3*) and are useful for determining whether a specific monthly observation is an outlier at a given significance level α . Multistep PI_s encompass a $1-\alpha$ prediction region that is a simultaneous PI for all observations registered up to a certain *h*-step and are useful in detecting systematic departures from historical patterns. We calculated $PI_{ss,h}$ as $\hat{y}_h = \pm t_{df,\alpha/2}\sqrt{PMSE_h}$ where $PMSE_h$ is the expected mean squared prediction error at step h and *df=N-DS-d-r*. In the calculation of multistep PI_s, we used a conservative approach based on a first-order Bonferroni inequality, whereby $Pl_{ms,h}$ is given as $\hat{y}_h = \pm t_{df,\alpha/2h}\sqrt{PMSE_h}$ and joint prediction intervals of, at least, $1-\alpha$ around the point forecasts are obtained.

4.0.Empirical Results

To decide on the presence of trend and time varying variances, the time plot of maximum energy consumption data in Figure 1 was inspected side by side with the ACF and PACF of the data as shown in Figure 2.

There is a systematic change in the time plot in Figure 1 which is not periodic. This indicates that the pattern of Ghana's total energy consumption is either decreasing or not. Total production was low after 1991 and we could attribute this to the low rainfall and increase in population and industries.. There was a sharp rise in production from 1997 to 1999, after which it drastically declined. In general, the trend of Ghana's total energy consumption follows an upward and downward movement. The figure exhibits a moving trend, hence there is the need to apply the method of differencing to attain stationarity since the trend describing the data shows non stationarity. The time series analysis of the energy consumption data was conducted using the R programme.

First, the behavior of the ACF for the time series was examined. The autocorrelation function of Ghana's total energy consumption is shown in Figure 2. The plot of the ACF function against the lag is called the correlogram. A trend in the data shows in the correlogram as a slow decay in the autocorrelation which depicts a downward slopping due to the exponential nature of the plot. It describes the correlation between values of Ghana's total energy consumption at different points in time, as a function of the time difference. The autocorrelation function is decreasing and that shows there is a trend in Ghana's total energy consumption data.

To remove the trend component from the data, the data was differenced. Figure 3 is a transformation of Ghana's total energy consumption using first differencing method. The observation does not revert to its mean value. The transformation of the data with the first differencing displays characteristics that suggest non stationary. Due to this it is necessary to make another transformation so as to produce a new series that is more compatible with the assumption of stationarity. In general, the first difference plot in Figure 4 reveal a little bit of variability. Hence the second differencing is employed.

Differencing the data the second time shows some variability and hence the data is still not stationary. Therefore a third differencing was applied to the data. A transformation was performed on Ghana's total energy consumption data using the third differencing method to remove the trend component in the original data, as shown in Figure 5. The observations move irregularly but revert to its mean value and the variability is also approximately constant. The data of Ghana's total energy consumption seemed to be approximately stable. Hence a seasonal ARIMA is expected of the process of the form $SARIMA(p,1,q)(P,1,Q)_{12}$. The KPSS unit root test for stationarity of the differenced energy consumption data is shown in Table 2. From Table 2, the p-value of 0.1 is greater than 0.05, so the stationarity holds for the final series.

The order of the model parameters p, q, P and Q were identified by visual inspection of ACF and PACF of the stationary process of the maximum energy consumption shown in Figure 6 to propose many possible models and the use of model selection criterion of AIC and BIC to pick the most appropriate model. The expectation was that the ACF in Figure 6 would cut at q+Qs. However a cut after lag 25 is noticed suggesting a moving average parameter of order one i.e. q=1 and a seasonal moving average parameter of order two i.e. Q=2. The plot exhibits an alternating sequence of positive and negative spikes. Such a pattern in the autocorrelation plot is signature of a sinusoidal model.

Similarly from the PACF in Figure 6, we notice a cut at lag 25 suggesting an AR parameter of order one i.e.p=1 and a Seasonal autoregressive parameter of order two i.e. P=2. Since the strategy was not to have mixed seasonal factors, two models were postulated from which, based on the model selection criterion of RSES, AIC and SBC, the best was selected.

The two models are SARIMA (1, 1, 1) (0, 1, 2) and SARIMA (1, 1, 1) (2, 1, 0). The search was extended to models around the two already mentioned. The result is shown in table 1. From table 1, we note that in terms of AIC and SBC, the SARIMA (1, 1, 1) (0, 1, 2) model performed best. However it is in competition with SARIMA (1, 1, 1) (1, 1, 2) that has the lowest RSES. This notwithstanding, SARIMA (1, 1, 1) (0, 1, 2) was chosen as the best in terms of model parsimony and performance based on AIC and BIC. The parameter values of the chosen model were estimated as shown(Table 2).

5.0.Parameter Estimation:

The model parameters were estimated by the method of Maximum Likelihood Estimates for each of the ARIMA model. From Table 3, the estimated coefficients of ARIMA (1, 1, 0) and ARIMA (0, 1, 1) are statistically significant. The estimated coefficients for SARIMA (1, 1, 1) is not statistically significant. SARIMA (1, 1, 0) is the best model with the minimum Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) statistics. The AIC, AICc and BIC are good for all the models but they favour SARIMA (1, 1, 0) model. The model is selected for forecasting.

We note that all the parameters are significant. The chosen model is mathematically of the form

$$(1-0.2378B)(1-B)(1-B^{12})\log y_t = (1-9172B)(1-6574B^{12}-0.2389^{12})a_t$$

$$(1-0.2378B)x_t = (1-0.9172B-0.6574B^{12}-0.2389B^{12}+0.2173B^{25})a_t$$

$$x_t = 0.2378x_{t-1}+a_t-0.9172a_{t-1}-0.2389a_{t-25}+0.2173_{t-26}$$

where

$$x_t = (1-B)(1-B^{12})\log y_t$$

To verify the suitability of the model, we plot the autocorrelation values of the residual against lag as shown in Figure 6. Inspection of Figure 6 reveals there is no spike at any lag indicating that the residual process is random. We complement with the portmanteau of Ljung and box. Computation of the Q value of the portmanteau test, using the first 25 autocorrelation values of the residual gives 18.468. When compared with tabulated chi square value of 32.7, with 21 degree of freedom and at 5% level of significance, we conclude that the model is a good fit. Table 3 shows the 2013 forecast using SARIMA (1, 1, 1) (0, 1, 2) and empirically observed data for the year 2012. A t-distribution test of equality of mean shows that the difference between the two means is not significant at 1% level of significance. We therefore conclude that the chosen model can adequately be used to forecast maximum energy consumption.

6.0.Conclusion

We have shown that time series ARIMA models can be used to model and forecast Maximum energy consumption. The identified SARIMA (1, 1, 1) (0, 1, 2) has proved to be adequate in forecasting maximum energy consumption for at least one year. Researchers will find this result useful in building energy consumption component into a general economic forecasting model. Also environmental manager who require long term energy consumption forecast will find the identified model very useful.

The univariate SARIMA model presented a good fit to the short time series of energy consumption, explaining most of its variance and adequately modeling the seasonality and correlation structure of the data. Taken together, these results indicate that SARIMA models should be adequate for data sets of monthly energy consumption in general, and not just those with larger sample sizes. The SARIMA model showed that energy consumption will continue to increase. The forecasted consumption levels will be a basis for government and Energy Commission to implement policies and programmes aimed at sustainable production of energy.

References

Anderson, R. L., (1942) Distribution of Serial Correlation Coefficient. *Annals of Mathematical Statistics*. Vol. 13, no. 1, pp. 1-13

Box, G, E. P. and Jenkins. (1976): *Time Series Analysis: Forecasting and Control*. Holden-Day, San Francisco, USA

Brockwell, P. J and Davis, R. A.(1991): Time Series: Theory and Method. *In Introductory Econometrics for Finance*. Cambridge University Press, UK

Hipel, K. J. W., McLeod, A. 1 and Lennox, W. (1977). Advances in Box-Jenkins Modeling: Model Construction. *Water resources Research. Vol.* 13, pp. 567-575

Ljung, G. M and Box, G. E. P (1978): On the Measure of Lack of Fit in Time Series Model. *Biometrika*, Vol. 65, pp. 297-303.

Mcleod, A. I., (1995): Diagnostic Checking of Periodic Autoregression Models With Application. *The Journal of Time Series Analysis*, Vol. 15, pp. 221-233

Albright, S. C., Winston, W., & Zappe, C. (2005). *Data analysis and decision making with Microsoft Excel*. Stamford, CT: South-Western College Publishing.

Bunn, D. W., & Farmer, E. D. (1985). *Comparative models for energy load forecasting*. New York, NY: Wiley.

Chase Jr., C. W. (1997). Selecting the appropriate forecasting method. *The Journal of Business Forecasting,* Vol. 2, no. 23, pp. 28–29.

Grossman, T. A. (1999). Why spreadsheets should be in OR/MS practitioner's tool kits. OR/ MS Today, Vol. 26, no. 4, pp. 20–21.

Harris, J. L., & Lui, L. M. (1993). Dynamic structural analysis and forecasting of residential energyity consumption. *International Journal of Forecasting*, Vo. 9, pp. 437–455.

Hartman, R. S. (1979). Frontiers in energy demand modeling. *Annual Review of Energy*, Vol. 4,pp. 433–466.

Kros, J. F. (2009). Spreadsheet modeling for business decisions. Dubuque, IA: Kendall/Hunt.

Radovilsky, Z., & Eyck, J. T. (2000). Forecasting with excel. The Journal of Business Forecasting, 19(3), 22–27.

Ragsdale, C. (2006). *Spreadsheet modeling and decision making*. Stamford, CT: South-Western College Publishing.

Savage, S. L. (2003). *Decision making with insight*. Boston, MA: Duxbury Press.

Stern, P. C. (1984). *Improving energy demand analysis*. Washington, DC: National Academy Press.

Table 1: KPSS Unit Root Test for Stationarity

KPSS Level	0.95
Truncation lag parameter	4
P-value	0.001

Table 2: Postulated Models and Performance Evaluation

Model	RSES	AIC	SBC
SARIMA(1,1,1)(2, 1, 0)	0.06814735	-782.4732	-752.4139
SARIMA(1,1,1)(0, 1, 2)	0.06574412	-845.3568	-802.0986
SARIMA(1,1,0)(1, 1, 2)	0.07084709	-609.7683	-772.1632
SARIMA(1,1,0)(1, 1, 2)	0.06978742	-839.7846	-728.3901
SARIMA(0,1,1)(0, 1, 2)	0.06524412	-798.3547	-738.3964
SARIMA(0,1,1)(1, 1, 2)	0.06579358	-734.0823	-752.4139
SARIMA(0,1,1)(0, 1, 2)	0.06326487	-642.3245	-761.9546
SARIMA(0,1,0)(1, 1, 2)	0.17576643	-756.2089	-657.8121
SARIMA(0,1,0)(0, 1, 2)	0.16556782	-772.6743	-674.0132

Table 3: Parameters B in the Model

	B	SEB	T-ratio	Approximate Probability
AR1	0.2378	0.06524	4.14711	0.0079434
MA1	0.9172	0.02716	28.05884	0.0000001
SMA1	0.6574	0.15794	5.347132	0.0000794
SMA2	0.2389	0.06872	3.097458	0.0547235

Table 4: Forecast for 2013

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Forecast	33.1	33.5	34.0	32.6	31.8	29.7	28.6	30.4	31.3	32.1	33.7	34.6
Observed	33.4	33.9	34.9	32.7	31.5	29.3	28.9	29.7	32.1	31.0	34.9	33.1
Difference	-0.3	-0.4	-0.9	-0.1	0.3	0.4	-0.3	0.7	-0.8	1.1	-1.2	1.5

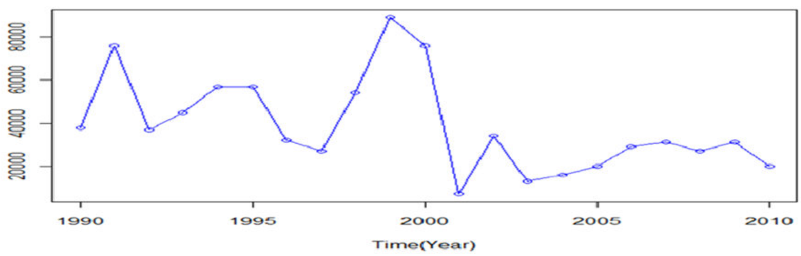

Figure 1: The time series plot of the total Energy Consumption in Ghana from 1990 to 2010.

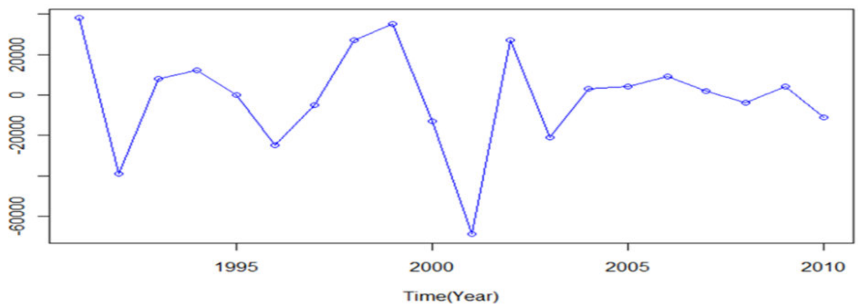

Figure 2: First differencing of Ghana's Energy Consumption from 1990 to 2010

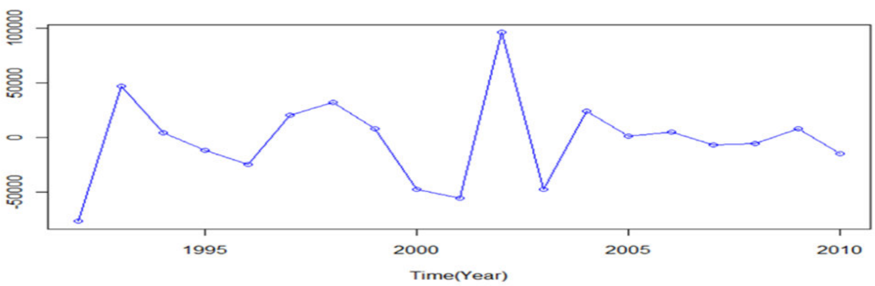

Figure 3: Second differencing of Ghana's Energy Consumption from 1990 to 2010

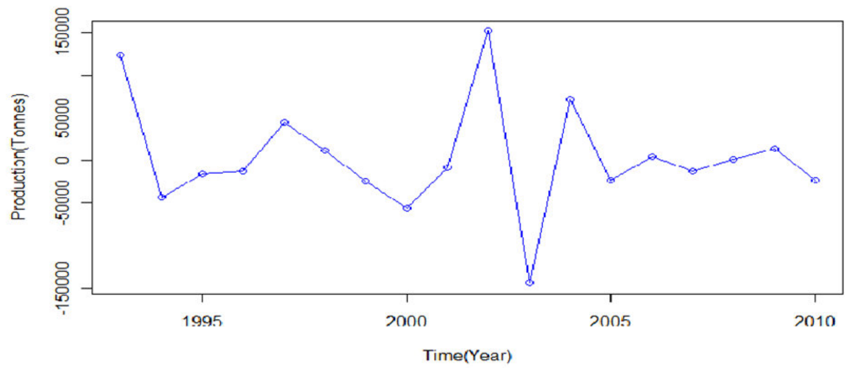

Figure 4: Third differencing of Ghana's Energy Consumption from 1990 to 2010

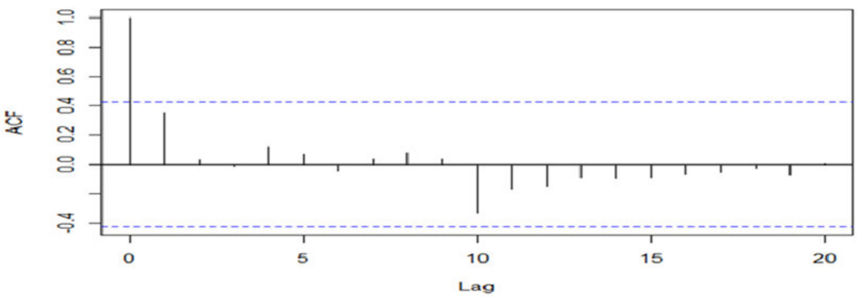

Figure 5: Autocorrelation function (ACF) of Ghana's Total Energy Consumption

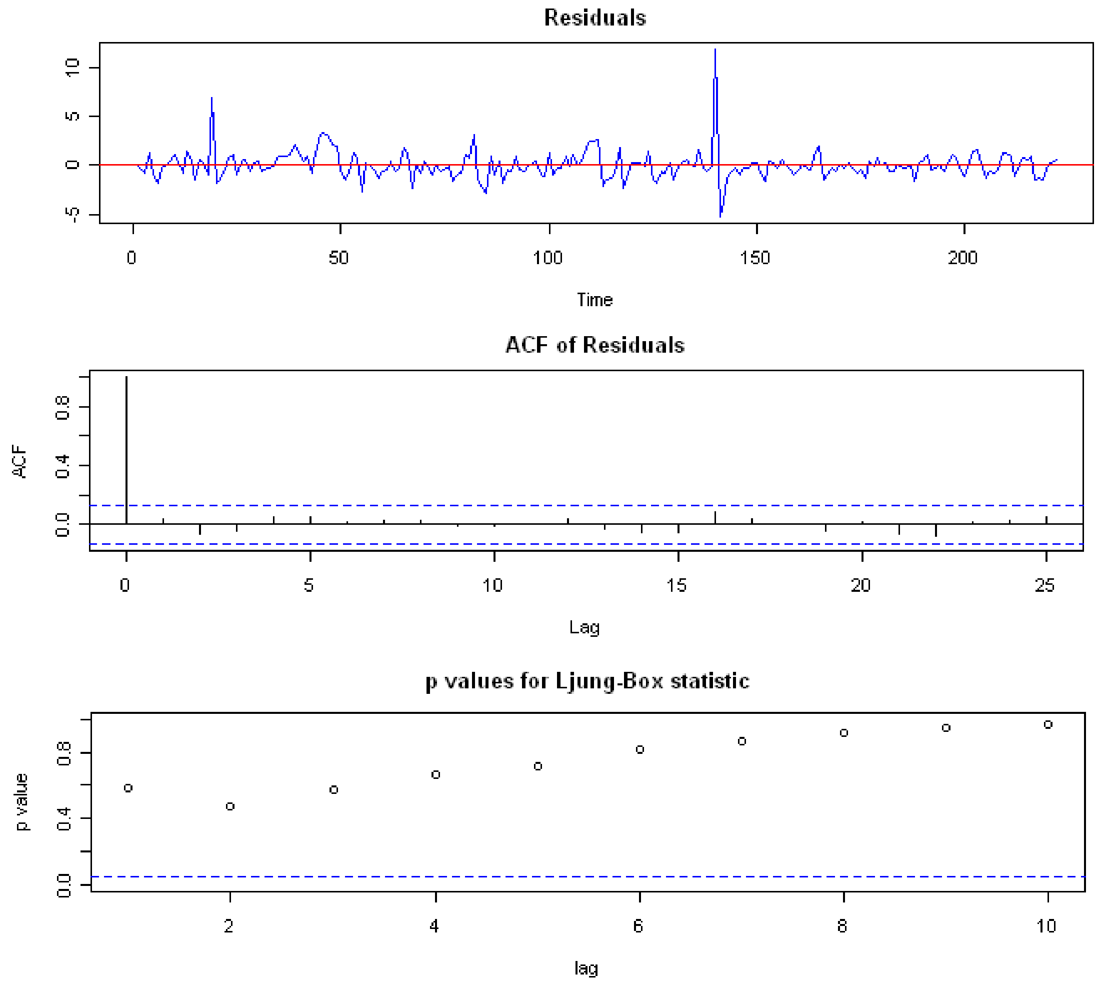

Figure 6: ACF and PACF Plots of Residuals