Modeling and forecasting demand for electricity in Zimbabwe using the Box-Jenkins ARIMA technique

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MODELING AND FORECASTING DEMAND FOR ELECTRICITY IN ZIMBABWE USING THE BOX-JENKINS ARIMA TECHNIQUE

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ABSTRACT

This study, which is the first of its kind in Zimbabwe, uses annual time series data on electricity demand in Zimbabwe from 1971 to 2014, to model and forecast the demand for electricity using the Box-Jenkins ARIMA framework. The study is guided by three objectives and these are: to analyze electricity consumption trends in Zimbabwe over the study period, to develop a reliable electricity demand forecasting model for Zimbabwe based on the Box-Jenkins ARIMA technique and last but not least, to project electricity demand in Zimbabwe over the next decade (2015 – 2025). Diagnostic tests indicate that X is an I (1) variable. Based on Theil's U, the study presents the ARIMA (1, 1, 6) model, the diagnostic tests further show that this model is stable and hence suitable for forecasting electricity demand in Zimbabwe. The selected optimal model, the ARIMA (1, 1, 6) model proves beyond any reasonable doubt that in the next 10 years (2015 – 2025), demand for electricity in Zimbabwe will continue to fall. Amongst other policy recommendations, the study advocates for the liberalization of the electricity power sector in Zimbabwe in order to pave way for more efficient private investment whose potential is envisaged to adequately meet the existing demand for electricity.

Contribution/ Originality:

This paper's primary contribution is finding that in the next 10 years (2015 – 2025), demand for electricity in Zimbabwe will continue to fall. This study should not be the end of the road, but rather an eye opener to Energy Economists and Electrical Engineers in Zimbabwe.

1. INTRODUCTION AND BACKGROUND

Energy is the driving force of any nation (Rahman *et al.*, 2018). Energy is an important ingredient for economic growth and development of any nation (Hussain *et al.*, 2016). Access to energy plays a critical role in achieving the Sustainable Development Goals (SDGs) by the year 2030 (Owusu and Asumadu-Sarkodie, 2016; Owusu *et al.*, 2016). Zimbabwe's 2030 Vision of "Upper-Middle-Income-Status" cannot be achieved without adequate access to energy, especially electricity. Electricity is one of the most essential and used form of energy and it is widely used for different kinds of needs, ranging from household to industrial uses (Lepojevic and Pesic, 2011). Electricity, as an especially high grade of energy, is a critical factor of production which facilitates technological advances and in turn stimulates the economy, by providing gains in productivity (Chipumho, 2011). Nowadays electricity is essential for economic development especially for the industrial sector (Lepojevic and Pesic, 2011). Many researchers, for example; Rakic (2001) and Abledu (2013) actually argue that there is a positive relationship between changes in Gross Domestic Product (GDP) and changes in electricity consumption in the sense that an increase in GDP leads to an increase in electricity demand. Electricity is considered to be the basis for the progress of civilization (Moreno-Chaparro *et al*, 2011) hence its great importance as a tool for the technological advancement and economic development of any society (Kandananond, 2011)(Moreno-Chaparro *et al*, 2011). Optimizing its distribution in terms of users and economic cost is currently a hot topic of research (Moreno-Chaparro *et al*, 2011).

Forecasting electricity consumption is a very important issue for governments and electricity related foundations of public sector (Hamzacebi, 2016). Such importance is attributed to the government's need for planning, especially for the future investments. Modeling electric energy consumption, as highlighted by Mucuk and Uysal (2009) is helpful in planning generation and distribution by power utilities. Hamzacebi & Es (2014) argue that the prediction of electricity demand is not only important for meeting future demand but also for engineering optimal energy policies for sustainable development. The forecasting is important for electricity power system planners and demand controllers in ensuring that there would be enough supply of electricity to cope with an increasing demand. Thus, accurate load forecasting can lead to an overall reduction of cost, better planning, maintenance scheduling and fuel management (Sabri and Humaira, 2011).

1.1. Zimbabwe Electricity Dynamics

Zimbabwe has been faced with energy challenges since the late 2000s, which saw massive power outages around the country of up to 16 hours a day (Makonese *et al.*, 2011). The country relies on a carbon intensive model to generate grid electricity for both the industrial and household sectors. About 43% of the country's electricity supply comes from burning coal, while 57% of the country's supply comes from renewable energy, specifically hydropower systems (Makonese, 2016). The supply of power in Zimbabwe basically comes from 2 sources, namely, local generation and imports. The local generation is sourced from Kariba Hydropower, Hwange Coal-fired power station and 4 small thermal power plants (i.e Hwange, Munyati, Bulawayo and Harare). Additional power is imported from the SAPP (Southern Africa Power Pool) countries, for which Zimbabwe is a member, namely, South Africa, Zambia, Democratic Republic of Congo (DRC) and Mozambique. Reductions in the supply of power in Zimbabwe are now a "normal problem". The local generation of power continues to dwindle due to lack of regular maintenance and the financial problems faced by ZESA (Zimbabwe Electricity Supply Authority, *a state owned company which dominates Zimbabwe's electricity sector*) and other players in the private sector (independent power producers). Electricity imports have been cut back owing to the inability of ZESA to settle its bills regularly. This has resulted in a mismatch of electricity supply visa-vis demand: demand is always not met. According to Chipumho (2011) the gap between supply and demand entails rolling load shedding daily. Since electricity, just like in any other country; is critical Zimbabwe's economic growth and development, persistent failure to meet demand has resulted in significant losses to the economy, especially in terms of productivity.

A number of studies have been done in an effort to model and forecast electricity demand around the world but no such study has been conducted in the case of Zimbabwe. There are a plethora of studies which have attempted to address various energy issues in Zimbabwe in trying to enhance sustainability in the energy sector, for example, Hemstock and Hall (1995); Mulugetta *et al.* (2000); Mungwena (2002); Mbohwa and Fukuda (2003); Nkomo and Goldstein (2006); Dube *et al.* (2007); Batidzirai *et al.* (2009); Jingura and Matengaifa (2009); Mumvuma (2010); Makonese *et al.* (2011); Chipumho (2011); Jingura *et al.* (2013); Mangizvo (2014); Makonese (2016) and Munyoro *et al.* (2016): while these studies are quite rigorous and well articulated, they have never attempted to explore the area of "modeling and forecasting electricity demand in Zimbabwe" and yet such studies are very critical for planning purposes in the electrical power sector in Zimbabwe. This piece of work, besides that it is the first of its kind in the case of Zimbabwe; contributes to Zimbabwe's energy demand-side management policy mechanics and investment decisions on energy infrastructure, especially with regard to power generation options to meet the projected electricity demand. The rest of the study is organized in chronological order as follows: literature review, materials & methods, findings and policy implication & conclusion.

1.2. Research Objectives

i. To analyze electricity consumption trends in Zimbabwe over the study period
ii. To develop a reliable electricity demand forecasting model for Zimbabwe based on the Box-Jenkins ARIMA technique.
iii. To project electricity demand in Zimbabwe over the next decade (2015 – 2025)

1.3. Statement of the Problem

Electricity is one of the most important commodities for the development of any nation (Ahuja and Tatsutani, 2009) and yet electricity shortage still remains a serious problem in Zimbabwe. This is attributed to the inability of the electricity supply to match consumer demand. For any country, especially developing countries such as

Zimbabwe, electricity demand forecasting is vital for increasing energy productivity. According to Kaytez *et al.* (2015) overestimation of electricity consumption would lead to superfluous idle capacity which means wasted financial resources, whereas underestimation would lead to higher operational costs for the energy supplier and would cause potential energy outages. Therefore, accurate and reliable modelling and forecasting of electricity demand in Zimbabwe is inevitably vital in order to avoid costly mistakes.

2. LITERATURE REVIEW

A plethora of scholarly papers have been published on this theme over recent decades. This could be attributed to the fact that electricity demand forecasting is gaining momentum in the field of Energy Economics. Given the main thrust of this research, Table 1 below provides a fair sample of studies undertaken more recently:

2.1. Literature Summary on Modelling and Forecasting Demand for Electricity

Table-1. Related Previous Studies

Author(s)/Year	Country	Period	Methodology	Main Findings
Abraham and Nath (2001)	Australia	August 2001 – May 2001	ARIMA, ANN, CGA, BPA	The Neuro-fuzzy system performed better than neural networks, ARIMA model and VPX forecasts
Suhartno and Endharta (2009)	Indonesia	1 August 2007 – 23 September 2007	Elman-RNN, ARIMA	The Elman-RNN (22, 3, 1) is the best method for forecasting hourly electricity load demand
Mati *et al.* (2009)	Nigeria	1970 – 2005	MA, MLR	The MA model is the optimal model for forecasting electricity demand
Nedzingahe *et al.* (2010)	South Africa	April 2003 – March 2008	Exponential Smoothing, ARIMA	The ARIMA model provides the best parameter estimates
Moreno-Chaparro *et al* (2011)	Colombia	1974 – 2008	MRA, NAR	MRA is the best model
Lepojevic and Pesic (2011)	Serbia	January 2006 – October 2011	Holt-Winter's model, SRM	Holt-Winter's model is the best
Kandananond (2011)	Thailand	1986 – 2010	ARIMA, ANN, MLR	ARIMA and MLR models might be preferable to the ANN model because of their simple structure and competitive performance
Makukule *et al.* (2012)	South Africa	2001 – 2009	Regression, SARIMA, RegSARIMA	The SARIMA model produces better forecasts
Erol *et al.* (2012)	Turkey	1970 – 2010	ARIMA, Holt-Winter's Method, ANN	Holt-Winter's Additive model performs the best
Chujai *et al.* (2013)	Thailand	December 2006 – November 2010	ARIMA, ARMA	The ARIMA model can represent the most suitable forecasting periods in monthly and quarterly. The ARMA model can represent the most suitable forecasting periods in daily and weekly
Safi (2013)	Palestine	January 2000 – December 2011	ANN, ARIMA	ANNs outperform the ARIMA model
Henao *et al.* (2013)	Colombia	August 1995 – April 2010	SARIMA, ANN	The Hybrid model obtained by fusing a SARIMA and a Generalized Single Neuron model is the best
Yasmeen and Sharif (2014)	Pakistan	January 1990 – December 2011	ARIMA, SARIMA, ARCH/GARCH	The ARIMA (3, 1, 2) is the most appropriate model

Saleh *et al.* (2014)	Indonesia	2000 – 2010	ARIMA, Exponential Smoothing Model	ARIMA is the optimal forecasting approach
Mabea (2014)	Kenya	1980 – 2009	ECM model	There is a cointegrating relationship between long-run price and income elasticity
Goel and Goel (2014)	India	1961 – 2013	MLR, TSM, ARIMA	ARIMA is the best model
Miswan *et al.* (2016)	Malaysia	2001 – 2015	ARIMA, DES	ARIMA is the more appropriate model
Sisman (2016)	Turkey	1970 – 2013	Grey model, ARIMA, MAED	ARIMA and Grey Models give better results than the MAED approach
Hamzacebi (2016)	Turkey	1987 – 2014	SGM, GM	SGM performs better than GM
Gajowniczek and Zabkowski (2017)	Poland	1 January 2008 – 31 December 2015	ANN, RF, SVM	SVM performs best in peak classification and ANN performs best in forecasting
Sigauke (2017)	South Africa	2009 – 2013	GAMs	GAMs have significantly improved level of accuracy in forecasting
Bozkurt *et al.* (2017)	Turkey	2014 – 2015	SARIMA, ANN	ANN fits better than SARIMA
Shilpa and Sheshadri (2017)	India	January 2016 – February 2016	ARIMA	ARIMA can be improved by developing the ARIMAX
Ezenugu *et al.* (2017)	Nigeria	2006 – 2014	MLR, QRM	The QRM without interactions was more accurate
Asumadu-Sarkodie (2017)	Ghana	1980 – 2013	ARIMA	Ghana's electricity consumption will grow from 8.52 billion kWh in 2012 to 9.56 billion kWh in 2030
Kartikasari and Prayogi (2018)	Indonesia	2007 – 2015	DMA, HSM, GM	The GM model is the best model
Castrillejo *et al.* (2018)	Uruguay	1 January 2007 – 31 December 2014	Pattern Method, Regression Analysis, Machine Learning	Machine Learning methods perform better
Rahman *et al.* (2018)	India	1947 – 2017	MLR, SRM, HM, BM, EM, ANN, SVM	The EM has the best fit
Wang *et al.* (2019)	Middle Africa	1994 – 2016	MGM, MECM, ARIMA, BP	Energy demand in Middle Africa will continue to grow at a rate of about 5.37%

Source: Authors' analysis from literature review (2019).

From Table 1 above, it is clear that, in the case of Zimbabwe, no study has been done so far to model and forecast electricity demand. This study is indeed the first of its kind in the case of Zimbabwe. It is imperative to note that, of the 29 previous studies reviewed, the majority (i.e 16 papers namely: Suhartno and Endharta (2009); Nedzingahe *et al.* (2010); Kandananond (2011); Makukule *et al.* (2012); Erol *et al.* (2012); Chujai *et al.* (2013); Safi (2013); Henao *et al.* (2013); Yasmeen and Sharif (2014); Saleh *et al.* (2014); Goel and Goel (2014); Miswan *et al.* (2016); Sisman (2016); Bozkurt *et al.* (2017); Shilpa and Sheshadri (2017) and Asumadu-Sarkodie (2017)) used the ARIMA approach in analyzing electricity demand. This is clear testimony to the fact that the ARIMA approach is a widely used technique when it comes to analyzing electricity demand, hence its use in this study. Table 1 also indicates that out of the 16 papers that employed the ARIMA model, the majority (i.e 9 papers namely: Nedzingahe *et al* (2010); Kandananond (2011); Makukule *et al.* (2012); Chujai *et al.* (2013); Saleh *et al.* (2014); Goel and Goel (2014); Miswan *et al.* (2016); Sisman (2016) and Shilpa and Sheshadri (2017)) consistently concluded that the ARIMA model is the appropriate technique for modeling and forecasting electricity demand. Other models that have been used to model and forecast electricity demand, as shown in Table 1, include ANNs, MRA, NAR, MLR, ARCH/GARCH, SGM, GM, DMA, HSM, DES and QRM amongst others. While the ARIMA model has been shown to take the lion's share in terms of use and popularity, some researchers have argued that the superiority of the ARIMA model cannot be overemphasized: for example, Erol *et al.* (2012) concluded that the Holt-Winter's Additive model performs better than the ARIMA model; Safi (2013) finalized that ANNs outperform the ARIMA model; as well as Bozkurt *et al.* (2017) who eventually noted that ANNs fit better than SARIMA models.

3. MATERIALS & METHODS

3.1. The Moving Average (MA) Model

Given:

$$X_t = \alpha_0\mu_t + \alpha_1\mu_{t-1} + \cdots + \alpha_q\mu_{t-q} \tag{1}$$

Where μ_t is a purely random process with mean zero and varience σ^2. As noted by Abledu (2013) equation (1) is explained as a Moving Average (MA) process of order q, commonly denoted as MA (q). X is the annual demand for electricity in Zimbabwe, measured in kWh at time t, $\alpha_0 \ldots \alpha_q$ are estimation parameters, μ_t is the current error term while $\mu_{t-1} \ldots \mu_{t-q}$ are previous error terms. In equation (1) X is being explained by the previous period values of error terms or disturbance terms. Thus:

$$X_t = \alpha_0\mu_t + \alpha_1\mu_{t-1} \tag{2}$$

Equation (2) is explained as an MA process of order one, commonly denoted as MA (1). This means that in equation (2), current values of X are explained by one previous period error term, the one realized in the previous period. Owing to the fact that previous error terms are unobserved variables, we may scale them so that α_0=1. Since we know that:

$$\left.\begin{matrix} E(\mu_t) = 0 \\ \forall\, t \end{matrix}\right\} \tag{3}$$

Equation (3) simply means that the expected value of the error term or the expectation of the error term is zero. Thus if we sum up all errors made over a particular period, the positive errors and the negative errors, we get zero.

Therefore:

$$E(X_t) = 0 \tag{4}$$

By assumption, equation (4) holds and this is explained to imply that equation (5) holds too. It means that when the expectation of X is zero, we observe constant varience in the series too.

and:

$$\mathrm{Var}(X_t) \cong \left(\sum_{i=0}^{q} \alpha_t^2\right)\sigma^2 \tag{5}$$

where μ_t is independent with a common varience σ^2. Hence, we can now re – write (Abledu, 2013) as follows:

$$X_t = \mu_t + \alpha_1\mu_{t-1} + \cdots + \alpha_q\mu_{t-q} \tag{6}$$

Equation 6 , which is the same as equation (1), can be re – written as follows using the summation notation:

$$X_t = \sum_{i=1}^{q} \alpha_i\mu_{t-i} + \mu_t \tag{7}$$

We may also write (Castrillejo *et al.*, 2018) as follows:

$$X_t = \sum_{i=1}^{q} \alpha_i L^i \mu_t + \mu_t \tag{8}$$

where L is the lag operator.

or as:

$$X_t = \alpha(L)\mu_t \tag{9}$$

where:

$$\alpha(L) = \theta(L)^1 \tag{10}$$

In equation (10), which is the algebraic manipulation of the above equations, the left-hand-side is as shown in equation (22), that is, it is a polynomial of order q; while the left-hand-side is as shown in equation (21), that is, it is a polynomial of order p.

3.2. The Autoregressive (AR) model

Given:

$$X_t = \beta_1 X_{t-1} + \cdots + \beta_p X_{t-p} + \mu_t \tag{11}$$

Equation (11) is explained as follows: $\beta_1 \ldots \beta_p$ are estimation parameters, $X_{t-1} \ldots X_{t-p}$ are previous period values of the X series and μ_t is as previously defined. X, in this case is being explained by its previous period values. Erol *et al.* (2012) is an Autoregressive (AR) process of order p, and is commonly denoted as AR (p); and can also be written, using the summation notation as follows:

$$X_t = \sum_{i=1}^{p} \beta_i X_{t-1} + \mu_t \tag{12}$$

Ezenugu *et al.* (2017) can be re – written as follows:

$$X_t = \sum_{i=1}^{p} \beta_i L^i X_t + \mu_t \tag{13}$$

or as:

$$\beta(L)X_t = \mu_t \tag{14}$$

where:

$$\beta(L) = \phi(L)^2 \tag{15}$$

or as:

$$X_t = \left(\beta_1 L + \cdots + \beta_p L^p\right) X_t + \mu_t \tag{16}$$

Thus, using the lag operator notation:

$$X_t = (\beta_1 L) X_t + \mu_t \tag{17}$$

is an AR process of order one, commonly denoted as AR (1).

3.3. The Autoregressive Moving Average (ARMA) model

As put forward by Box & Jenkins (1970) an ARMA (p, q) process is simply a combination of AR (p) and MA (q) processes. Thus, from Abledu (2013) and Erol *et al.* (2012); an ARMA (p, q) process can be specified as follows:

$$X_t = \beta_1 X_{t-1} + \cdots + \beta_p X_{t-p} + \mu_t + \alpha_1 \mu_{t-1} + \cdots + \alpha_q \mu_{t-q} \tag{18}$$

or as:

$$X_t = \sum_{i=1}^{p} \beta_i X_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \tag{19}$$

Equations (18) and (19) convey the same message: ARMA processes are simply AR and MA processes combined in that order. There is always an advantage over combing AR and MA models to form ARMA models because ARMA models perform better than single AR or MA models.

From Castrillejo *et al.* (2018) and Ezenugu *et al.* (2017). Henao *et al.* (2013) can also be written as follows:

$$\phi(L)X_t = \theta(L)\mu_t \tag{20}$$

where $\phi(L)$ and $\theta(L)$ are polynomials of orders p and q respectively, simply defined as:

$$\phi(L) = 1 - \beta_1 L \ldots \beta_p L^p \tag{21}$$

$$\theta(L) = 1 + \alpha_1 L + \cdots + \alpha_q L^q \tag{22}$$

3.4. The Autoregressive Integrated Moving Average (ARIMA) model

Making prediction in time series using univariate approach is best done by employing the ARIMA models (Alnaa & Ahiakpor, 2011). A stochastic process X_t is referred to as an Autoregressive Integrated Moving Average (ARIMA) [p, d, q] process if it is integrated of order "d" [I (d)] and the "d" times differenced process has an ARMA (p, q) representation. If the sequence $\Delta^d X_t$ satisfies an ARMA (p, q) process; then the sequence of X_t also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d X_t = \sum_{i=1}^{p} \beta_i \Delta^d X_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \tag{23}$$

which can also be re – written as follows:

$$\Delta^d X_t = \sum_{i=1}^{p} \beta_i \Delta^d L^i X_t + \sum_{i=1}^{q} \alpha_i L^i \mu_t + \mu_t \tag{24}$$

where Δ is the difference operator, vector $\beta \in \mathbb{R}^p$ and $\alpha \in \mathbb{R}^q$. Equations (23) and (24) show the generalized ARIMA set-up framework. The generalized ARIMA model is frequently used in empirical work because most variables, especially financial and economic variables are non-stationary.

3.5. The Mechanics of the Box – Jenkins Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018i).

3.6. Data Collection

Electricity demand forecasting is carried out for various time frames, from short-term to long-term forecasting (Taylor, 2008). Long-term electricity demand forecasting ranges from several months to several years ahead (Hyndman and Fan, 2008). This research focuses on long-term electricity demand forecasting for Zimbabwe and is apparently based on 44 annual observations of electric power consumption in terms of kWh per capita (which accounts for the production of power plants and combined heat and power plants less transmission, distribution, and transformation losses and own use by heat and power plants), i.e. 1971 – 2014. The data is extracted from the World Bank online database. In this study, we denote electric power consumption as variable X. According to Ismail *et al.* (2009) long-term electricity demand forecasting is important for strategic planning which involves capacity expansion, power system planning, power security and supply reliability.

3.7. Diagnostic Tests and Model Evaluation

3.7.1. Stationarity Tests: Graphical Analysis

Figure-1. Graphical Analysis

Source: Author's Own Computation

3.7.2. The Correlogram in Levels

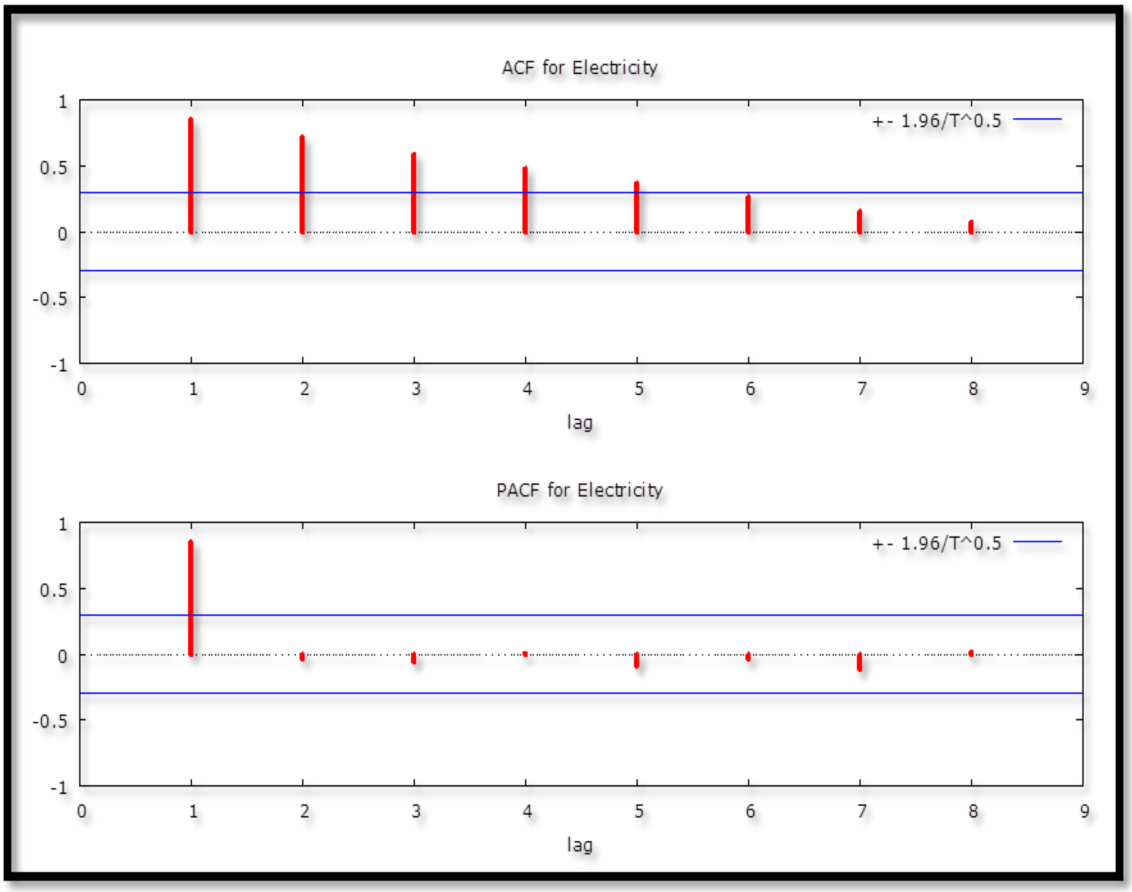

Figure-2. Correlogram in Levels

Source: Author's Own Computation

3.7.3. The ADF Test

Table-2. Levels-intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
X	-0.797643	0.8097	-3.592462	@1%	Not stationary
			-2.931404	@5%	Not stationary
			-2.603944	@10%	Not stationary

Source: Author's Own Computation

Table-3. Levels-trend & intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
X	-3.662662	0.0360	-4.186481	@1%	Not stationary
			-3.518090	@5%	Stationary
			-3.189732	@10%	Stationary

Source: Author's Own Computation

Table-4. Without intercept and trend & intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
X	-0.464611	0.5082	-2.619851	@1%	Not stationary
			-1.948686	@5%	Not stationary
			-1.612036	@10%	Not stationary

Source: Author's Own Computation

As shown in Figures 1 and 2 and Tables 2 to 4, variable X is non-stationary in levels.

3.7.4. The Correlogram at 1st Differences

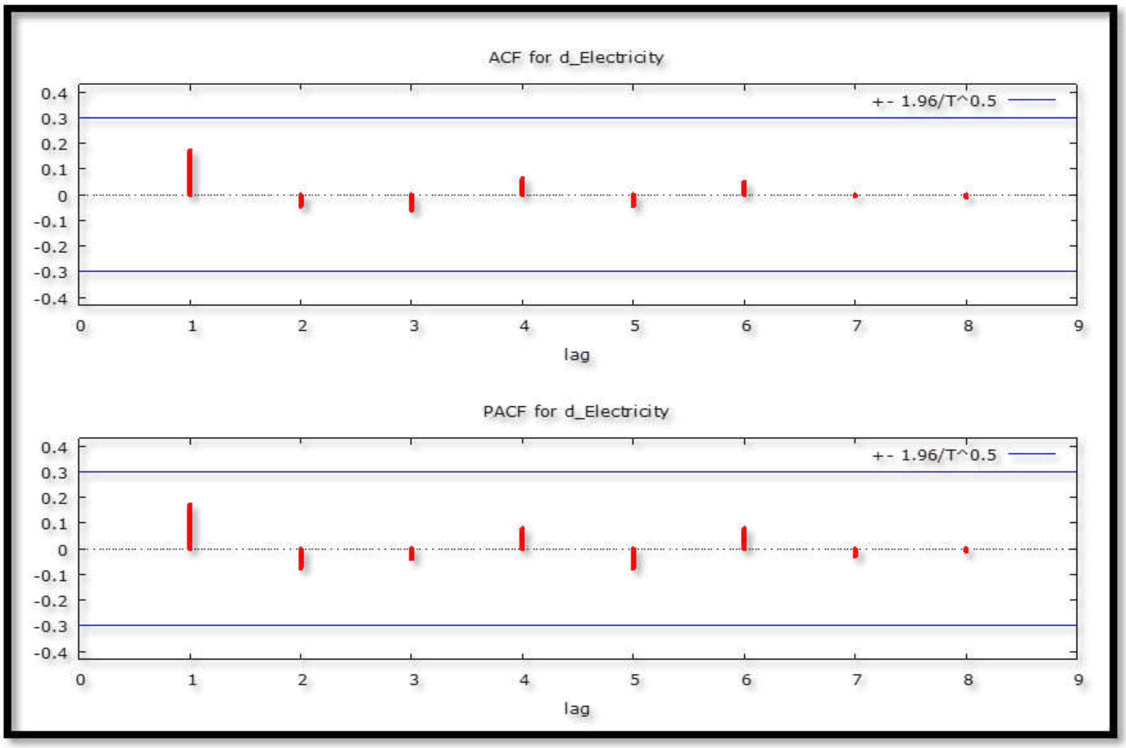

Figure-3. Correlogram at 1st differences

Source: Author's Own Computation

Table-5. 1st Difference-intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
X	-6.168913	0.0000	-3.596616	@1%	Stationary
			-2.933158	@5%	Stationary
			-2.604867	@10%	Stationary

Source: Author's Own Computation

Table-6. 1st Difference-trend & intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
X	-6.226863	0.0000	-4.192337	@1%	Stationary
			-3.520787	@5%	Stationary
			-3.191277	@10%	Stationary

Source: Author's Own Computation

Table-7. 1st Difference-without intercept and trend & intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
X	-6.148205	0.0000	-2.621185	@1%	Stationary
			-1.948886	@5%	Stationary
			-1.611932	@10%	Stationary

Source: Author's Own Computation

Figure 3 and Tables 5 to 7 indicate that X is an I (1) variable.

3.7.5. Evaluation of ARIMA Models (without a constant)

Table-8. Evaluation of ARIMA models

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	472.6416	0.95948	-2.4594	43.332	55.338	5.3379
ARIMA (0, 1, 2)	472.6406	0.95943	-2.4512	43.329	55.342	5.3368
ARIMA (0, 1, 1)	**470.6428**	0.95955	-2.4696	43.334	55.332	5.339
ARIMA (0, 1, 3)	474.1473	0.95307	-2.5258	42.579	55.192	5.2326
ARIMA (0, 1, 4)	475.3261	0.94978	-2.2173	42.645	54.777	5.2843
ARIMA (0, 1, 5)	477.2045	0.94855	-2.3175	42.745	54.668	5.2919

ARIMA (1, 1, 0)	470.8373	0.96293	-2.412	43.254	55.431	5.3301
ARIMA (2, 1, 0)	472.5276	0.95754	-2.5423	43.208	55.277	5.3207
ARIMA (3, 1, 0)	474.5135	0.9568	-2.5702	43.088	55.267	5.3017
ARIMA (4, 1, 0)	475.8578	0.95147	-2.2383	42.505	55.002	5.2565
ARIMA (5, 1, 0)	477.6047	0.95208	-2.368	42.511	54.861	5.2642
ARIMA (1, 1, 6)	481.1125	**0.94433**	-2.2499	42.55	54.648	5.2546
ARIMA (1, 1, 7)	483.0802	0.94527	-2.228	42.624	54.655	5.2658
ARIMA (1, 1, 8)	485.0764	0.9461	-2.3068	42.63	54.646	5.2715
ARIMA (1, 1, 2)	474.6345	0.95944	-2.5122	43.313	55.312	5.3378
ARIMA (1, 1, 3)	475.4071	0.94762	-2.4204	42.267	54.788	5.2133
ARIMA (1, 1, 4)	477.2030	0.94758	-2.2835	42.647	54.667	5.2782
ARIMA (1, 1, 5)	479.1985	0.94779	-2.3038	42.683	54.661	5.2826
ARIMA (2, 1, 1)	474.5238	0.95733	-2.5512	43.177	55.274	5.3157
ARIMA (3, 1, 1)	475.9676	0.95104	-2.5346	42.331	55.003	5.209
ARIMA (4, 1, 1)	477.4736	0.94978	-2.2792	42.532	54.793	5.2644
ARIMA (5, 1, 1)	479.4474	0.95014	-2.3351	42.595	54.771	5.2717
ARIMA (2, 1, 4)	479.2153	0.94613	-2.2483	42.407	54.696	5.2462
ARIMA (2, 1, 5)	481.1937	0.94668	-2.2818	42.564	54.67	5.2675

Source: Author's Own Computation

Table 8 shows the main model evaluation statistics and these are AIC (Akaike's Information Criterion), Theil's U, Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and the Mean Percentage Error (MAPE). All these statistics are equally important, however; in this study we mainly base our analysis on U. A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018n). Theil's U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018l). The rule of thumb dictates that the MAPE must lie below 10% if a model has good forecast accuracy. The study will only consider Theil's U as the criteria for choosing the best model and thus the ARIMA (1, 1, 6) model is selected.

3.8. Residual & Stability Tests

3.8.1. Residual Correlogram

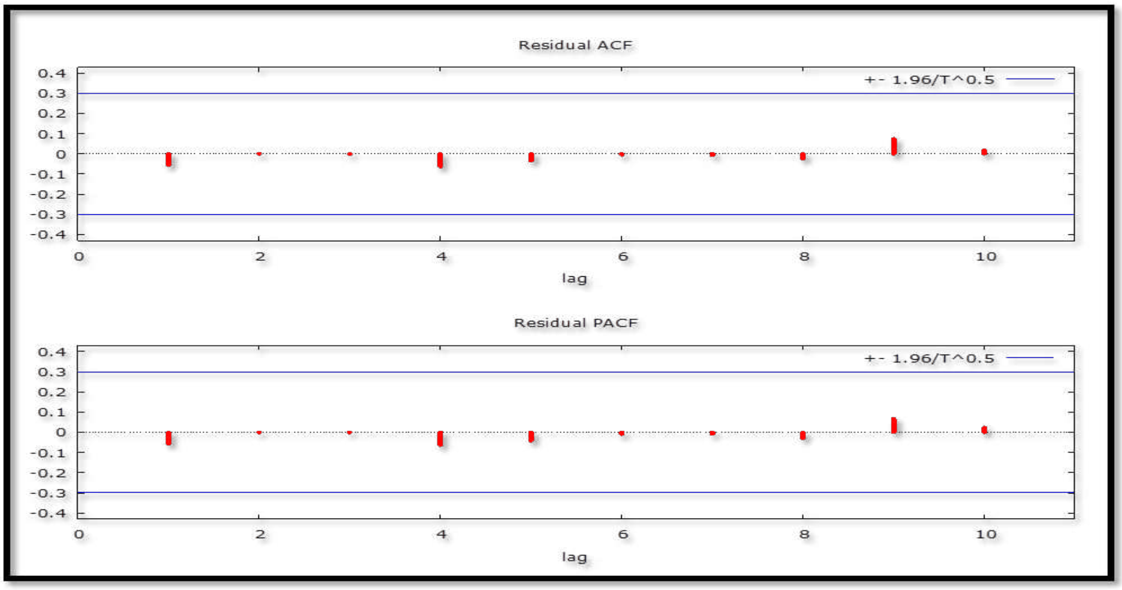

Figure-4. Residual correlogram

Source: Author's Own Computation

3.9. ADF Tests of the Residuals of the ARIMA (1, 1, 6) Model

Table-9. Levels-intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.705943	0.0000	-3.596616	@1%	Stationary
			-2.933158	@5%	Stationary

		-2.604867	@10%	Stationary

Source: Author's Own Computation

Table-10. Levels-trend & intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.668921	0.0000	-4.192337	@1%	Stationary
			-3.520787	@5%	Stationary
			-3.191277	@10%	Stationary

Source: Author's Own Computation

Table-11. Without intercept and trend & intercept.

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.693829	0.0000	-2.621185	@1%	Stationary
			-1.948886	@5%	Stationary
			-1.611932	@10%	Stationary

Source: Author's Own Computation

Figure 4 and Tables 9 to 11 show that the residuals of the ARIMA (1, 1, 6) model are stationary.

3.10. Stability Test of the ARIMA (1, 1, 6) Model

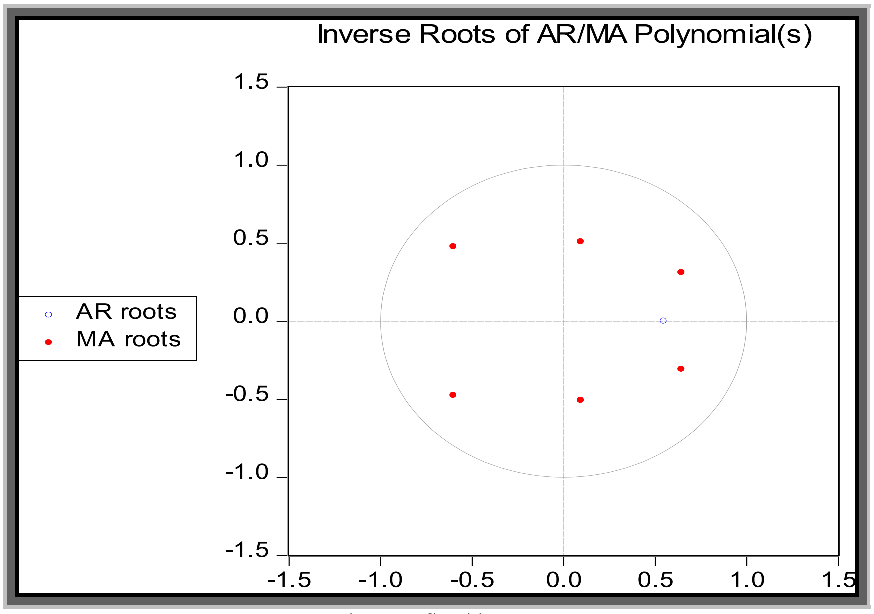

Figure-5. Stability test

Source: Author's Own Computation

Figure 5 is a graphical representation of the inverse roots of the ARIMA (1, 1, 6) model. For a stable model, the roots must lie right inside the unit circle, otherwise the model may be regarded as unstable and hence unsuitable for forecasting purposes. Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, then we can conclude that the chosen ARIMA (1, 1, 6) model is stable and indeed suitable for forecasting demand for electricity in Zimbabwe.

4. FINDINGS

Table-12. Descriptive statistics

Description	Statistic
Mean	821.23
Median	866
Minimum	531
Maximum	1038
Standard deviation	137.81
Skewness	-0.98509

Excess kurtosis	-0.083044

Source: Author's Own Computation

As shown in Table 12 above, the mean is positive, i.e 821.23 kWh. The median is 866 kWh. The maximum is 1038 kWh and was realized in 1976. This could be explained by the high level of industrial activity in the country during that period. The minimum is 531 kWh and was realized in 2009 and this could easily be attributed to the economic crisis of the 1997 – 2008 decade that saw closure of many companies and high capital outflows. Reduction in electricity consumption over this period can be explained by lack of financial resources to purchase electricity from the households' perspective, due to lack of financial resources. Since skewness is -0.98509, it implies that variable X is negatively skewed and non-symmetric. Excess kurtosis is -0.083044 and simply indicates that X is not normally distributed.

5. RESULTS PRESENTATION

Table-13. Results

ARIMA (1, 1, 6) Model:

$$\Delta X_{t-1} = 0.549492\Delta X_{t-1} - 0.279282\mu_{t-1} - 0.165667\mu_{t-2} - 0.0807181\mu_{t-3} + 0.207306\mu_{t-4} - 0.095002\mu_{t-5} + 0.0803435\mu_{t-6} \quad (25)$$

Variable	Coefficient	Standard Error	z	p-value
AR (1)	0.549492	1.56785	0.3505	0.726
MA (1)	-0.279282	1.56628	-0.1783	0.8585
MA (2)	-0.165667	0.457671	-0.362	0.7174
MA (3)	-0.0807181	0.160972	-0.5014	0.6161
MA (4)	0.207306	0.214141	0.9681	0.333
MA (5)	-0.095002	0.314819	-0.3018	0.7628
MA (6)	0.0803435	0.158456	0.507	0.6121

Source: Author's Own Computation

Equation (25) is the optimal model, the ARIMA (1, 1, 6) model. Striking to note is that all the AR and MA components are statistically insignificant. Usually for electricity demand models, this does not really matter. What matters most, is the forecasting accuracy of the model.

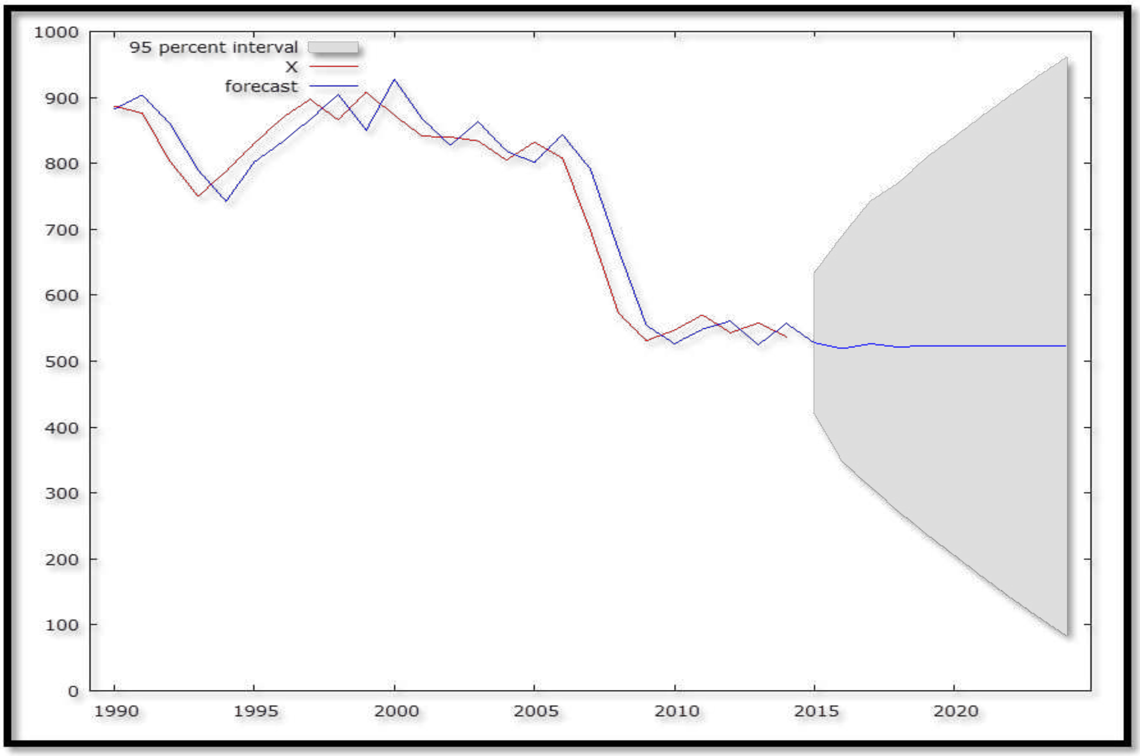

Figure-6. Forecast graph

Source: Author's Own Computation

Predicted Demand for Electricity in Zimbabwe (2015 – 2025)[1]

Table-14. Tabulated out-of-sample-forecasts

Year	Prediction	Std. error	95% interval
2015	527.663	53.8267	(422.164, 633.161)
2016	519.027	87.0168	(348.477, 689.577)
2017	526.221	110.095	(310.439, 742.003)
2018	521.434	126.644	(273.216, 769.652)
2019	523.365	145.230	(238.720, 808.011)
2020	522.822	161.497	(206.293, 839.350)
2021	522.523	177.943	(173.760, 871.285)
2022	522.359	193.872	(142.377, 902.340)
2023	522.268	209.045	(112.548, 931.988)
2024	522.219	223.426	(84.3109, 960.127)
2025	522.191	237.061	(57.5605, 986.823)

Source: Author's Own Computation

Predicted Electricity Demand in Zimbabwe (2015 – 2025).

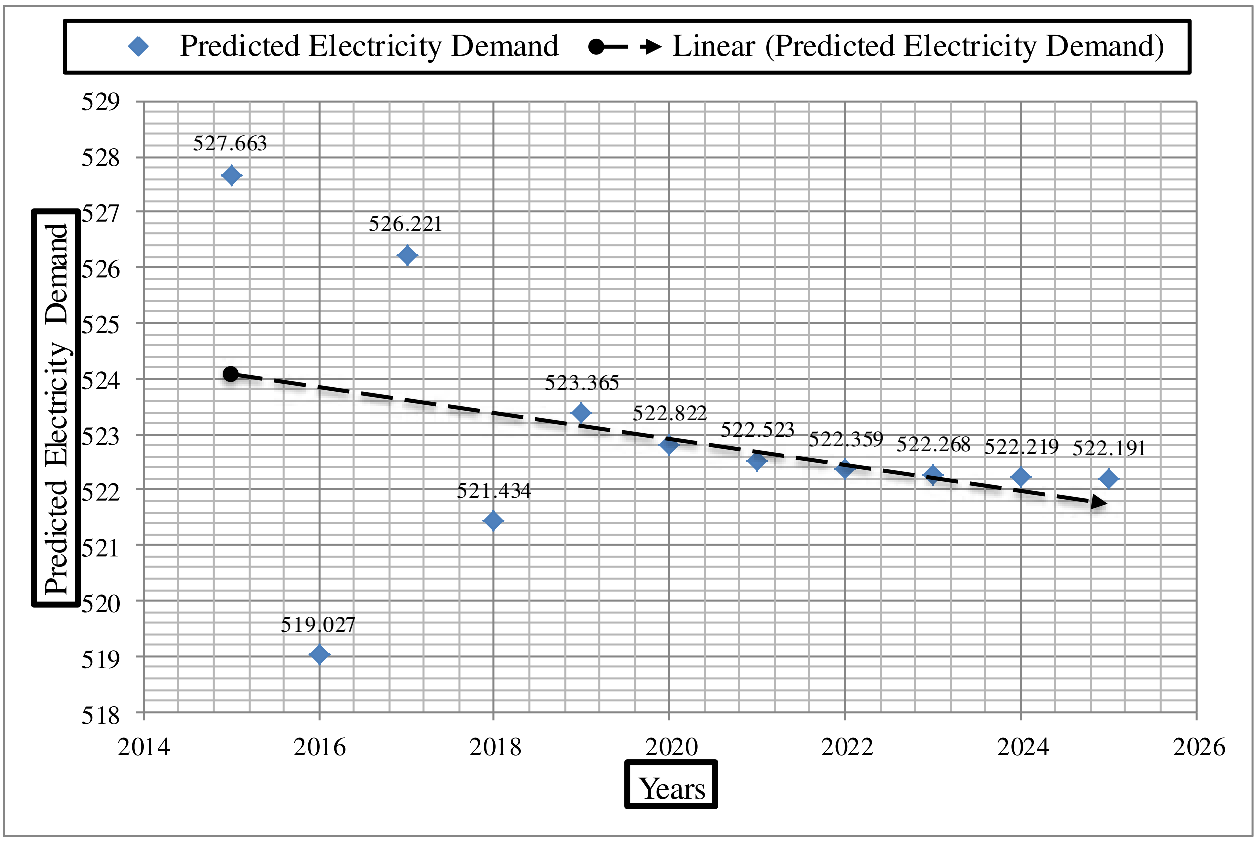

Figure-7. Out-of-sample forecasts in graphical form

Source: Author's Own Computation

Table 13 shows the main results of the optimal model, the ARIMA (1, 1, 6) model. The both AR and MA components are insignificant. The insignificance of the AR component implies that previous period electricity consumption is not important in explaining long-run demand for electricity in Zimbabwe. The insignificant MA components imply that there are no shocks to electricity demand in Zimbabwe. The ARIMA (1, 1, 6) model points to the fact there are other factors that account for electricity demand in Zimbabwe, for example, uncompetitive pricing

[1] For 95% confidence intervals, z (0.025) = 1.96.

of electricity as a commodity, inadequate refurbishment of power stations and so on. Figure 6 and 7 and Table 14 show predicted demand for electricity in Zimbabwe over the period 2015 to 2025. It is clear that demand for electricity in Zimbabwe is likely to continue falling over the period 2015 to 2025. These findings are inconsistent with Munyoro *et al.* (2016) argument that Zimbabwe's demand for electricity is growing against a declining power generation capacity. The results rather indicate that Zimbabwe's demand for electricity is falling along with a persistently dwindling power generation capacity. The fact that electrical power generation is greatly constrained in Zimbabwe does not imply that it is demand for electricity which is increasing. This study shows that demand for electricity in Zimbabwe reached its annual peak of 1038 kWh in 1976, and since then, electricity consumption has declined until now and the ARIMA (1, 1, 6) model proves beyond any reasonable doubt that in the next 10 years (2015 – 2025), demand for electricity in Zimbabwe will continue to fall. Here are some of the main reasons why the demand for electricity in Zimbabwe is likely to continue falling over the forecasted period:

i. Slowdown in economic activity (Online Herald Newspaper, 2016). It is a well-known fact that when the economy is poorly performing, as is the case with Zimbabwe, demand for electricity tends to go down because the industrial sector (which is usually the main consumer of electricity) is literally shut-down and the incomes of economic agents are significantly reduced. Many researchers agree that there is a positive relationship between electricity consumption and economic growth, for example, Rakic (2001) and Abledu (2013). What it simply means is that the falling demand in electricity in Zimbabwe is caused by the persistent economic ills prevalent in the country. If the economy of Zimbabwe is revived and stimulated, the demand for electricity is expected to rise significantly just like what happened over the period 1971 – 1976, as shown in Figure 1 above.
ii. The rise of distributed generation in Zimbabwe: These days households and firms are getting off the power grid in the sense that most people are increasingly opting for the use of solar energy, i.e solar panels on rooftops, where electricity is produced and consumed on-site. The study therefore concurs with the arguments made by Batidzirai *et al.* (2009) and Makonese (2016) that the demand for solar PV and solar water heaters is expected to increase in the near future and that this will reduce both electricity demand and expenditure, while on the other hand, improving the general living standards for communities.
iii. Zimbabweans are arguably changing their life-styles, especially with regards to saving money. For example, there is no "power bill" from rooftop solar panels! The other important reason for a change in life-style is hinged on (i) highlighted above. The other reason for a change in life-style, especially the shift towards the use of solar panels, could be that people have no more confidence in ZESA as their main supplier of electricity, and where possible, they would opt for alternative energy sources such as the use of solar panels amongst others.
iv. Embracing energy-saving appliances and lighting, for example, use of LED light bulbs which use up to 90% electricity less as compared to incandescent light bulbs.

5.1. Further Research

Further studies should seek to address the following issues that still remain unexplored:

i. There is need to further research on short-term electricity demand modeling and forecasting in Zimbabwe. According to Taylor (2008) short-term forecasts are needed by both generators and retailers of electricity, especially during periods of abnormal peak load demand. In Zimbabwe, just like in any other country, accurate short-term electricity demand forecasts are envisaged to serve the purpose of load-shifting between transmission substations. Thus short-term electricity demand forecasting is quite essential for load management.
ii. There is also need to further research on medium-term electricity demand modeling and forecasting in Zimbabwe. Ismail *et al.* (2009) states that medium-term electricity demand forecasting is important for risk assessment and maintenance planning.

iii. A similar study can be done using a different methodological approach, for example, making use of Hybrid Models and Artificial Neural Networks.

iv. The empirical nexus between electricity consumption and economic growth in Zimbabwe.

6. POLICY IMPLICATION & CONCLUSION

Researchers nowadays cannot afford to turn a blind eye on the need to model and forecast electricity demand. The objectives of this study were 3-fold and these are: to analyze electricity consumption trends in Zimbabwe, to develop a reliable electricity demand forecasting model for Zimbabwe based on the Box-Jenkins ARIMA technique and to project electricity demand in Zimbabwe over the next decade (2015 – 2025). Based on Theil's U, the ARIMA (1, 1, 6) model has been chosen as the optimal model for forecasting long-term electricity demand in Zimbabwe. The study basically recommends that entities involved in the production and distribution of electricity in Zimbabwe, ought to adapt production and distribution capacities in order to avoid power outages. The paper also advocates for the liberalization of the electricity power sector in order to pave way for more efficient private investment whose potential is envisaged to adequately meet the existing demand for electricity: this recommendation is motivated by the fact that power outages in Zimbabwe are a common feature despite falling demand for electricity. This study is not the end of the road, but rather an eye opener to Energy Economists and Electrical Engineers on the way forward.

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