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Electricity Price Forecasting for Port Harcourt Distribution Company in Nigeria

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ABSTRACT
The objective of this study was to forecast electricity price for Port-Harcourt Electricity Distribution Company and specifically examine the impact of inflation rate, interest rate, exchange rate and cost of fuel on the price of electricity using regression model and autoregressive integrated moving average (ARIMA) model suggested by Box and Jenkins (1976). The forecasting performance of the estimated model was between 2008 and 2016. The analyses were carried out with the aid of EViews and Excel software.

The study used the ordinary least square (OLS) technique for estimation purposes. On the basis of the various diagnostic and selection evaluation criteria, the best model was selected for forecasting Port-Harcourt electricity Distribution Company electricity price. The study found ARIMA (2, 1, 3) as the most appropriate model under model identification, parameter estimation, diagnostic checking and forecasting electricity price. In-sample forecasting was conducted and the estimated ARIMA model remarkably tracked the actual forecast during the sample period.

The study found that interest rate significantly influenced electricity price at 10%, while other variables did not have significant influence on electricity price. The major inference that can be drawn from this study is that inflation rate, exchange rate, and cost of fuel are not important determinant of electricity price in Port-Harcourt Electricity Distribution Company. Interest rate is the only significant factor among the four factors in this study at 10%, which makes it to be weakly significant.

I. CHAPTER ONE:INTRODUCTION

1.1 Background to the Study

Electricity price forecasting here after known as (EPF) is a branch of energy forecasting focused on predicting electricity prices. According to Weron (2006), “Over the last 15 years electricity price forecasts have become a fundamental input to energy companies’ decision-making mechanisms at the corporate level”. Weron (2014) provided a landmark result by studying published papers on EPF from the year 1989 - 2013. The first major publication was in 2005, as of 2013 the topic seemed to have flooded the research community. While the amount of citation is still rising, probably a fresh basic urge like the deregulation that took place in 1990s or the worse instability of electricity prices in the mid-2000s is needed in order to boost electricity price forecasting to another level of publication concentration.

According to Bowerman, O’Connell and Koehler (2005), “A prediction state of affairs of future events and situations are called forecasts, and the act of making such predictions is called forecasting”. Forecasting is the basic facet of decision making in different areas of life. Forecasting is the process of making predictions about an event whose outcome is unknown at present. In other words, forecasting is stating how the future will look like. In today’s trade world, forecasting is of significant meaning and interest for most companies since an accurate forecast can provide any business unit in a given market a strategic advantage over its competitors. It is the main tool for assessment making and energy companies are not exempted.

EPF is an indispensable tool for an energy company in order to invest properly (Pelin & Javier, 2011). The price of the electricity is the major variable in decision making in energy markets. Therefore, it is very exciting from an energy company’s point of view to be able to anticipate electricity price.

The worldwide deregulation of the power industry has made EPF to become an important

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area of research. According to Bunn (2004) "Unlike electricity demand cycle, electricity price series can display variable means, major volatility and significant spikes". Very many approaches has been developed for electricity price forecasting over the last ten years on the basis of the need of the industry (Bastian, Zhu, Banunarayanan, & Mukerji, 1999). According to Zhang, Gao, Wu and Liu (2012), "Game-theory based models which focus on the impact of bidder strategic performance on electricity prices and regression models". Also is the artificial intelligence model (Georgilakis, 2007).

Deregulation in the power industry is happening all over the world, even Nigeria has also toe the line by starting to privatize and deregulate with the introduction of competition in its power industry. According to Odubiyi and Davidson (2010), "Economic, environmental issues, regulatory challenges, and changing public perception have contributed to the thoughtful changes or reform being embarked upon by developed and developing nations.

The methods of setting the price of electricity in Nigeria have not been defined precisely since the inception of the Nigerian electricity sector. Electricity prices had generally been cut down because it was perceived to be a public welfare service to be provided by the Government, hence subsidy.

To set the price of electricity guideline in Nigeria, the Multi-Year Tariff Order (MYTO) was established by the Nigerian Electricity Regulatory Commission (NERC). MYTO has been in existence since 2008. Before the 2008 Multi-Year Tariff Order (MYTO), in spite of the increase in the price of gas, the tariff has been rigid for years. Fascinatingly, more than 50 per cent of Nigeria's power is generated from gas. The Power Holding Company of Nigeria (PHCN) tariff was set in February, 2008, with regards to the setting methodology, the company still recorded about ₦2 billion debt. Hence, the inadequate and unstable electricity service. The system of pricing discouraged the entrance and operation of investors with profit orientation. For a stable and predictable electricity price, there is a call for an appropriate procedure. In order to get this done, the Nigerian Electricity Regulatory Commission (NERC) was created to develop a novel tariff regime based on the sector's revenue necessities. Hence, the new tariff regime that took effect in the course of a Multi–Year Tariff Order (MYTO) in 2008. In this study, we forecast the price of electricity of Port - Harcourt Distribution Company in Nigeria.

1.2 Statement of the Problem

According to Weron (2006), "the development of deregulation and the introduction of competitive electricity markets have been reshaping the landscape of the traditionally monopolistic and government-controlled power sectors". All through various countries, spot and derivative contracts are the rules used in trading price of electricity. However, since electricity is different from other types of product in terms of its uniqueness, economically it cannot be stored and power system steadiness requires a steady equilibrium between production and usage. No other market has the unique distinctiveness of price variability that exist on daily, weekly and often on annual basis. Risk can be reduced drastically and profits can be maximized fully when a power utility firm is able to forecast electricity prices with a reasonable level of precision, especially in balancing production and consumption.

According to Joskow (2001), "the costs of over / under contracting and then selling/buying power in the balancing (or real-time) market are typically so high that they can lead to enormous monetary losses or even insolvency". In Nigeria, to the best of my knowledge there is no adequate prior research study on EPF. Hence, there is a need to study the emergence of competitive deregulated electricity market in Nigeria.

There is a need to study the dynamics, behavior and impact of some economic factors such as inflation rate, interest rates, exchange rates, and technical factor like fuel price, on Port Harcourt electricity prices**.**

There is a need to empirically model and forecast Port Harcourt distribution company electricity prices, which to the best of my knowledge, has never been done before.

There is a need to empirically investigate regression model and Autoregressive Integrated Moving Average (ARIMA) to model electricity prices.

Therefore, this research is set to forecast the electricity price of C3 (Maximum Demand) of the commercial class of Port Harcourt Electricity Distribution Company.

1.3 Research Questions

To guide the study, the following research questions have been formulated.

1. Does inflation rate of the country significantly influence electricity price of commercial class of Port Harcourt Distribution Company?
2. Does interest rate have significant impact on electricity price of commercial class of Port Harcourt Distribution Company?

3. Does exchange rate significantly affect electricity price of commercial class of Port Harcourt Distribution Company?
4. Does cost of fuel significantly influence electricity price of commercial class of Port Harcourt Distribution Company?

1.4 Objectives of the Study

The broad objective of the study is to examine the application regression model and Box-Jenkins ARIMA in forecasting electricity price in Port Harcourt Distribution Company. This study's specific objectives are to:

1. Find out whether inflation rates of the country significantly influence electricity price of commercial class of Port Harcourt Distribution Company.
2. Determine whether interest rates significantly influence electricity price of commercial class of Port Harcourt Distribution Company.
3. Examine if exchange rates significantly impact on electricity price of commercial class of Port Harcourt Distribution Company.
4. Investigate whether cost of fuel significantly affect electricity price of commercial class of Port Harcourt Distribution Company.

1.5 Research Hypotheses

The following research hypotheses stated in null form were tested:

H_{01}: The inflation rate of the country does not significantly influence electricity price of commercial class of Port Harcourt Distribution Company.

H_{02}: Interest rates in the country does not significantly influence electricity price of commercial class of Port Harcourt Distribution Company.

H_{03}: Exchange rate does not significantly impact on electricity price of commercial class of Port Harcourt Distribution Company.

H_{04}: Cost of fuel does not significantly affect electricity price of commercial class of Port Harcourt Distribution Company.

1.6 Scope of the Study

In this research work, the area of study is Port Harcourt. This study described the application of Autoregressive Integrated Moving Average and regression in forecasting electricity price of C3 (Maximum Demand) of the commercial class of Port-Harcourt Electricity Distribution Company.

There are eleven distribution companies in Nigeria and there are five major classes of customers. The study forecast the price of electricity for the commercial class of Port Harcourt electricity Distribution Company.

The study made use of the Port-Harcourt Electricity Distribution Company price of electricity from 2008 to 2016 being a 9-year period to forecast price of electricity. The choice of the period of forecast is specified for accuracy.

1.7 Significance of the Study

In today's business environment, forecasting is of significant value and interest for most companies, since an accurate forecast can provide any business unit in a given market a strategic benefit over its competitors.

In broad terms the study demonstrates that EPF in Port Harcourt will enhance energy companies in identifying the patterns, trend and variation in price of electricity.

Having a better grasp on what will happen in the future will also serve as a vital input to for top management decision making particularly for energy companies.

The study also reveals the impact of exchange rate, inflation rate, interest rate and cost of fuel on the price of electricity in the Distribution Company. Specifically the study will benefit energy companies, investors, academics, statisticians, consumer and the general public.

Unlike other developed countries, to the best of our knowledge, there have been studies on electricity demand and supply but none on EPF. However, we believe it can be done in Nigeria also. Hence, a need for further research in this area of study.

1.8 Limitation of the Study

Due to the fact that the scope of the study is restricted to Port Harcourt electricity Distribution Company, whereas it sought to make generalization to all distribution companies in Nigeria. Another limitation for the study is:

1. Limited data availability: Before the year 2008 in Nigeria, the tariff setting framework of commercial electricity was not clear enough. Hence, we were only able to source for data from 2008 - 2016, which was used for the forecast. It is believed that the available nine year period yielded a good and reliable result since the autoregressive integrated moving average (ARIMA) was one of the models used. ARIMA is suitable when little about past information is known.

II. CHAPTER TWO

LITERATURE REVIEW

2.1Introduction

In this chapter, the concept, theories and empirical studies on electricity price forecasting were reviewed. Also examined, is the theoretical and practical underpinnings for assessing the variations in EPF, customers classification and distribution Companies in Nigeria.

2.2 Conceptual Review of Electricity Price Forecasting

According to Montgomery, Johnson and Gardiner (1990), "The intention of forecasting is to decrease risk in decision making and reduce unanticipated cost". One of the most important works of an electric power utility is correct. The goal of an energy company is to maximize the value of its assets. In order to achieve this goal within a reasonable risk margin, business opportunities and risks need to be identified. To be able to identify them, it is necessary to forecast the behavior of the markets of interest and especially the evolution of certain variable, like the price of electricity. The prices of electricity are the main variables in decision making in energy markets. Therefore, it is very interesting from an energy company's point of view to be able to forecast the electricity price whether in the short, medium or long-term.

The study of the electricity market must take into account the special characteristics of the power system such as:

1. Electricity cannot be stored in the same way as other goods. It can be stored in batteries or in the form of energy by pumping water into storages, although storage possibilities are inadequate.
2. Small disturbances can lead to main consequences in the power system. Frequency or voltage deviations can lead to cascading failures and thus supply interruptions.
3. Losses are involved in transmission, generation and transportation of electricity. Hence, there is need to take them into consideration since losses occur on lines (Smith, 2010).

2.3 Factors Influencing Price Forecasting

Economic as well as technical factors cause fluctuation of prices especially in a deregulated market. (Nitin & Mohanty, 2015). Economic factors include factors such as: interest rates, exchange rates, inflation rates, politics, and depreciation, while technical factors include: weather, fuel cost and generation reserve (Nitin & Mohanty, 2015). Other factors that affect the price are:

Demand of electric power

The aggregate demand is a significant factor in determining spot price. Studies conducted revealed that increase in system demand also leads to increase in price.

Condition of weather

Environmental circumstances and daily heat affect electricity demand. Once electricity demand is affected, spot price will also be affected.

Cost of fuel

One of the most important factors influencing electricity spot price is fuel cost. The higher the fuel cost, the higher the electricity price.

Availability of Transmission facility

A generator located close to customers brings about enhanced capacity.

Generation Reserves

An important factor for electricity price is enough and a sustaining level of reserves. Unexpected increase in demand can be catered for by adequate reserve. However, customers would be faced with lack of energy received if there is available reserve.

Generally, in Nigeria, the cost of producing electricity is more than electricity prices. According to Odubiyi and Davidson (2010) "The methodology in setting electricity prices in Nigeria has been ill-defined and opaque since the Nigerian electricity sector was established. Electricity was considered a civic welfare service to be provided by the government".

Before 2008, the methodology for setting electricity price as to what it cost to transform, transmit and distribute a Mega Watt (MW) of power to customers was not transparent. In the entire electricity sector, prices were set formerly by the National Electric Power Authority which didn't reflect the key variables such as inflation rate, interest rate, exchange rate, fluctuations in demand, increase in the price of natural gas and capital expenditure. As soon as the prices were agreed upon, the presidency approves the tariffs. Then, there was enormous under investment in the whole value chain in the power industry. Also, owing to the fact that enough budgetary provisions did not capture capital expenditure in the power sector and tariffs were too little as to develop the power sector, at least to take care, sustain and maintain infrastructure. Presently, the key factors that go into the model are majorly macroeconomic and

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sector specific (load factor, losses, fuel prices, depreciation, etc). There are other key inputs which include projections of generation capacity, capital expenditure, operating expenditure, etc.

2.3.1 Inflation Rate

Inflation refers to the persistent and the continuous increase in the general level of prices of goods and services in an economy. It is no gainsaying that diverse economy in many parts of the world experience inflation. The differences lie in the timing, causes, duration and in their prevailing economic conditions. Suffice to say then that, be it developed, developing or underdeveloped, economies of countries of the world do witness rise in price. For some economies it could be mere fluctuations, while for some others, it is consistent and continuous. The changes in the price level of market basket of consumer goods and services purchased by household is measured by the consumer price index (CPI). Inflation is measured by the yearly percentage change in a CPI.

According to McConnel and Brue (2008), " Inflation is best referred to as an increase in price, where inflation decreases purchasing power of a currency increases". It is rare for aggregate for inflation to cause aggregate demand to increase faster than aggregate supply, hence, the cost of goods and services will be increased. Government deficit, expansion of bank's interest rates and increase of foreign demand can be linked to the difference between total demand and supply (Haberler, 1960). The price of goods and the price of labour can as well be increased by inflation, hence the cost of goods and selling price increases (Sukimo, 2000). Consumer Price Index (CPI), Wholesale Price Index (WPI), and Implicit Price Index are indicators of inflation (Majalah, 2002). The rate of inflation in Nigeria as measured by the National Bureau of Statistics (the US - CPI for dollar denominated costs).

In the MYTO, the rate of inflation is used to ensure that investors are well remunerated against increasing cost of doing business in Nigeria and personnel in the power sector are paid in commensurate to their living wages.

2.3.2 Exchange Rate

The rate at which one currency would be exchanged for another is referred to as Exchange rate. It is also termed as the value of one nation's currency in comparison to a different currency. Foreign exchange market is where the exchange rate is determined, which is available to very many buyers and sellers, and where currency trading increases, exchange rate is a value that a currency has compared to another currency (Krugman, 2001). Tiwari (2003) stated that 'exchange rate can be divided into two categories, fixed exchange rate and flexible exchange rate'. The Government set the fixed exchange rate, while flexible exchange rate is set by the market in which there could be interference by the Government to even out the monetary (Kuncoro, 2001).

Fuels which are sold in dollars and priced locally are used in determining electricity price in national currency. The impact of exchange rates and fuel prices on electricity prices represents a topic which has not been comprehensively investigated. From a general point of view, Blomberg and Harris (1995) pointed out that commodity price movements can be a reaction to swings in dollar exchange rates as opposed to a signal of general inflation pressures.

From 2005-2007, Muñoz and Dickey (2009) studied the relationship between Spanish electricity spot prices, fuel prices and the dollar exchange rate. It was revealed that the variables were co-integrated, implying the existence of a long-run equilibrium among them. A transmission of volatility from the dollar exchange rate and fuel prices to Spanish electricity prices was also observed, although the price of electricity remained unchanged.

The MYTO model assumes the official Central Bank of Nigeria exchange rate. The key variable in wholesale electricity tariff is the exchange rate as lot of components and services in the power sector are procured offshore. Moreover, the dollar is used to denominate the price of gas.

2.3.3 Fuel Cost

The price of natural gas as well as the cost of transporting the natural gas to the power plant is referred to as the fuel cost. The pass-through cost is the price of gas.

Amano and Norden (1998) conclude that the macroeconomic role of fuel prices may become more significant as other energy prices, such as gas, coal and to a smaller degree, electricity are occasionally priced to contend with fuel in foreign markets. Therefore, the price of fuel instability is reflected in general energy price fluctuations. Besides, Sadorsky (1999) constructs observed models in order to reveal fuel prices and volatility affect the market asymmetrically, or in other words, variations in fuel prices heavily influence the economy but change in the economy have an insignificant influence on fuel prices.

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To set the wholesale and the retail prices in the Nigerian electricity market, the MYTO is used, with the following ideology and rules.

a. Recovery of Cost/viability of finance.
b. Investment Signals
c. Assurance and constancy
d. Effective system use
e. Risk allocations
f. plainness and minimization of cost
g. Performance improvement incentive
h. Clearness/equality
i. Suppleness/Sufficiency
j. Political and social objective

2.3.4 Interest rate

The amount due per period, as a percentage of the amount lent, deposited or borrowed is referred to as interest rate. The principal sum determines the total interest, the compounding rate of recurrence, and the period taken over which it is borrowed or deposited. It is referred to as the proportion of an amount loaned which a lender requires as interest to the borrower, usually articulated as a yearly percentage Patterson (1999). It is the fee a bank or other lender charges to lend out its money, or the rate a bank pays its saver for taking custody of money in an account. It varies according to:

a. the directives of the government to the central bank to achieve the government's goals.
b. the main amount borrowed or lent.
c. the investment maturity term.
d. the borrowers perceived default probability.
e. the market demand and supply.

According to Patterson (1999) in Economics theory, “interest rate can be explained as a value that is gained in the effort of a value that has been saved or invested. These rates will reveal the interaction between exchanges of money”. The Central Bank influence the short term rates, hence, accordingly money is being monopolized. However, the long term rates reveals the state of the present economy and the possibility of inflation. These two rates work together and they are being linked together. In energy investment, long-term interest rates play an important role. (just like other choices of investment). According to Pierre (2015) “interest rates greatly influence the costs of capital for energy projects and are thus potentially an important factor in the competitiveness of energy technologies using renewable energy to produce electricity”. The interest rates impact on the costs of producing electricity with different technologies, using renewable and non-renewable energy. He further asserted the impact of interest rate on electricity production cost. Pierre (2015) studied impact of interest rate on electricity production cost and concluded that the lower the interest rate environment is, the more viable energy technology is.

2.4 Forecasting Horizons

In literature, it is normal to talk about the short, medium and long term electricity price forecasting, as there is no agreement on what the threshold should be. EPF in the short term generally have to do with forecasting from a few minutes up to a few days ahead, and is of importance in day to day market operation. The medium term vary from few days to a few months ahead and they are generally preferred for balance sheet calculation, management of risk and derivatives pricing. In very many cases, distributions of prices over certain future time periods are used for evaluation and not on the actual point forecasts.

According to Ventosa , Baíllo, Ramos and Rivier (2005), “the main goal of long term EPF with lead times measured in months, quarters or even years is investment profitability analysis and planning, such as determining the future sites or fuel sources of power plants”.

According to Söder and Amelin (2010), from the view of a producer of electricity, the goal is to maximize the value of its assets during a certain period of time, while keeping the risk within certain limits. Depending on how far in the future the studied period is, different models need to be considered since the level of detail varies with the time horizon. For instance, the day ahead planning for the production in a certain unit needs to be on a more detailed level than for longer time horizons (several years for example). A common way of separating planning periods is to divide them into three major time horizons.

2.4.1 Short-Term Horizon

Short term planning is of significance to producers when deciding which production units need to be started up or shut down. The short term planning includes daily planning and weekly planning. The time span considered vary from 24 hours up to one week. As the time horizon considered involves forecasting in the near future a highly detailed model is needed. Uncertainties such as variation in the demand, weather or water inflow are lower since the forecasts are likely to be more accurate than for longer time horizons. For hydro power, the goal of the electricity producer is to plan the discharge and evolution of the water reservoir according to electricity price variations induced by the variations in the demand during the day and the week (Nitin & Mohanty, 2015).

This planning is prepared close to the period it will be used, so the uncertainty of variables such as the water inflow are lower than for longer time horizons (Nitin & Mohanty, 2015).

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2.4.2 Medium - term horizon

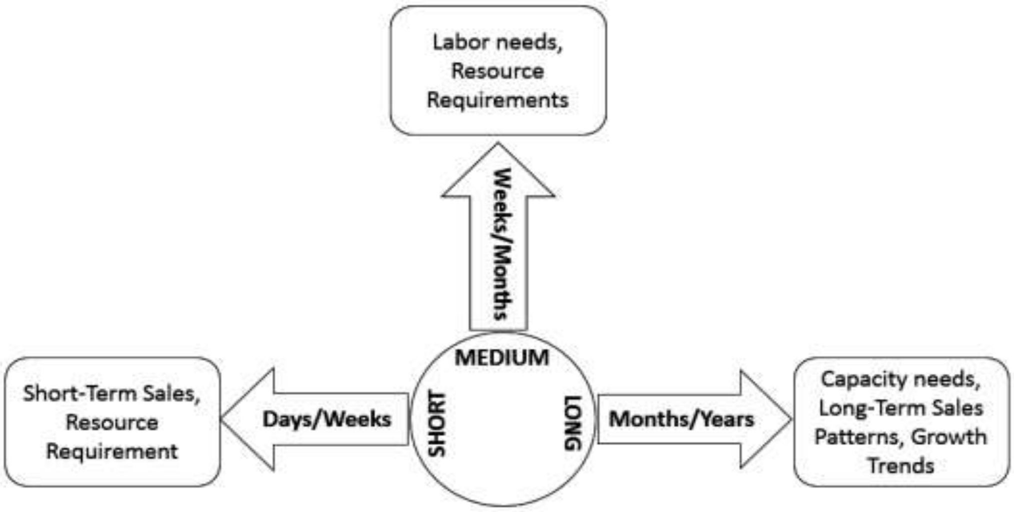
The medium-term planning includes seasonally planning and yearly planning. The time horizons considered vary from three months up to twelve months. For hydro power, the goal of the producer is to make a decision on how much water will be stored in the reservoir and how much water will be discharged for production of electricity according to seasonal variations of electricity prices. This planning is mostly affected by the uncertainty on the inflows and demand (Nitin & Mohanty, 2015).

2.4.3 Long term horizon

The time horizons considered for the long-term planning vary from two years up to thirty years. Such long time horizons are usually used to plan water saving policies in the big reservoirs (up to 2-3 years) or for long term strategic decisions (up to 30 years). Long-term strategic decisions can involve investments such as buying or building a power plant, entering a new market, grid expansion, etc. but can also involve de-investments. Long-term horizon is of interest in this study.

Forecasting Horizons

Figure1



Source: (Nitin & Mohanty, 2015)

2.5 Steps to Forecasting

According to Shaibu (2016) the goal of proactive companies is to improve their forecasting and simultaneously, to develop sound flexible production control based on forecast principles and characteristics. Different firms forecasts in very many ways, the whole process depend on intuition and skills. There are models, such as least squares regression analysis, semi averages, moving averages, and exponential smoothing. Regardless of the method that is used to make the forecast, the same eight overall procedures that follow are used.

- Determine the use of the forecast i.e the objectives we are trying to obtain?
- Select the items or quantities that are to be forecasted.
- Determine the time horizon of the forecast.
- Select the forecasting model or models.
- Gather the data needed to make the forecast.
- Forecasting model validation.
- Make use of the forecasting models.
- Execute the result.

According to Shaibu (2016), “these steps present a logical way of initiating, designing, and implementing a forecast system”.

2.6 Price of Electricity in Nigeria

The present population of Nigeria is more than 170 million, it grow by 6% yearly. (Okoro & Chikuni, 2007). There are 36 states in Nigeria with the Federal Capital Territory (FCT). Hence, the history of the sector is very important and it cannot be over emphasized. Electricity started in Nigeria in 1896 after the installation of two mall generating sets to serve the then colony of Lagos. Only about 60kW is the total power of the generator, that was after England had experienced power supply for about fifteen years. Nigeria established electricity commission in 1946 to take control of the responsibility of supply of electricity in Lagos State (Okoro & Chikuni, 2007). The Electricity Corporation of Nigeria(ECN) was established through an Act of Parliament in 1951. However, a union was later made in 1972 to structure the National Electric power Authority (NEPA). More than two decades before 1999, there was no significant investment in infrastructure, this is because there was no new plant and the existing ones were not maintained. In 2001, there was a decrease in production capacity. Besides, less than twenty out of about one hundred of the installed generating units were working (Sambo, 2008).

NEPA was responsible for the power sector in Nigeria. NEPA was solely in charge of the generation, transmission and distribution of electricity until year 2005 that the deregulation and the power reform took place under the administration of President Olusegun Obasanjo whereby the organization's name was changed to Power Holding Company of Nigeria (PHCN). In March 2005, when President Olusegun Obasanjo endorsed the Power Sector Reform Bill into law, private companies were given privilege to take part in electricity generation, transmission and distribution. The deregulation of PHCN was to consists eleven distribution companies (DISCOS), six generating companies (GENCOS), and one transmission company (TRANSCOS). The inefficiency of NEPA was to be taken care of by PHCN and to develop power system in Nigeria Mohiuddin (2011).

The MYTO was based on the new entrant cost profile for generation companies and the building block approach to electricity pricing of transmission and distribution services, all with an underlying set of pricing principles and cost assumptions.

In addition, different pricing options was provided by the Nigerian Electricity Regulatory Commission for arriving at tariffs of power generators. According to Saheed(2013), "the assumptions reviewed include available generation capacity, forecast of electricity demand, expansion of the transmission and distribution networks, capital expenditure, operating costs, fuel costs, interest rates, weighted average cost of capital, exchange rates, revenue collection efficiencies, inflation rates and subsidies".

2.7 Customer Classification

The responsibility of the Distribution Companies (Disco) is to determine the amount each customer pays so as to realize revenue.

Customer Tariff Classes are:

Residential Customers (R class): A consumer using a building as residence house, flat or multi-storied.

Commercial Customers (C class): this class belongs to customers that uses hi/her premises absolutely for factory and production of goods.

Industrial Customers (D Class): Buildings used for manufacturing goods which include welding and ironmongery

Special Class: Customers such as agriculture and agro-allied industries, water boards, religious houses, government and teaching hospitals, government research institutes and educational establishments.

Street lighting (S class).

2.8 Distribution Companies

Local Distribution Company (LDC) was the result of the divestiture of the Federal Government from PHCN. According to Eleanya, Ezechukwu, and Ofurum (2010), each company will be responsible for handling electricity distribution in each state or region. The company was structured as follows.

1. The Abuja Distribution Company plc
2. The Benin Distribution Company plc
3. The Eko Distribution Company plc
4. The Enugu Distribution Company plc
5. The Ibadan Distribution Company plc
6. The Ikeja Distribution Company plc
7. The Jos Distribution Company plc
8. The Kano Distribution Company plc
9. The Kaduna Distribution Company plc
10. The Port Harcourt Distribution Company plc
11. The Yola Distribution Company plc

2.9 Models of Electricity Price Forecasting

Weron (2014) "A variety of methods and ideas have been tried for EPF over the last 15 years, with varying degrees of success. They can be broadly classified into six groups".

2.9.1 Multi-agent models

Multi-agent models simulate the operation of a system of heterogeneous agents interacting with each other, and build the price process by matching the demand and supply in the market (Weron, 2014). This class includes cost-based models (Bunn & Derek, 2004).

Equilibrium or game theoretic approaches like the Nash-Cournot framework, supply function equilibrium, strategic production-cost models and agent-based models (Weron, 2014). Multi-agent models generally focus on qualitative issues rather than quantitative results. They may provide insights as to whether or not prices will be above marginal costs, and how this might influence the players' outcomes. However, they pose problems if more quantitative conclusions have to be drawn, particularly if electricity prices have to be predicted with a high level of precision.

2.9.2 Fundamental models

Fundamental methods try to capture the basic physical and economic relationships which are present in the production and trading of electricity (Weron, 2014). The functional associations between fundamental drivers are postulated, and the fundamental inputs are modeled and predicted independently, often via statistical, reduced-form or computational intelligence techniques. In general, two subclasses of fundamental models can be identified: parameter rich models (Bunn, 2004) and parsimonious structural models of supply and demand (Ventosa et al., 2005). One of the popular model classes in the literature that predict or model electricity prices is the one relating to parsimonious stochastic models.

The assumption of stationarity is satisfied if the error term has a zero mean and a constant variance. However, since many variables, including electricity price time series, exhibit trends, different variances, and correlation between past and future values, first-differencing is used to provide a new stationary time series. There are two major challenges arise in the practical execution of fundamental models, they are data availability and incorporation of stochastic fluctuations of the fundamental drivers. In building the model, specific assumptions about physical and economic relationships in the marketplace, and therefore the price projections generated by the models are very sensitive to violations of these assumptions.

2.9.3 Reduced-form Models

Reduced-form models characterize the statistical properties of electricity prices over time, with the ultimate objective of derivatives valuation and risk management (Weron, 2014). Their main intention is not to provide accurate hourly price forecasts, but rather to replicate the main characteristics of daily electricity prices, like marginal distributions at future time points, price dynamics, and correlations between commodity prices. If the price process chosen is not appropriate for capturing the main properties of electricity prices, the results from the model are likely to be unreliable. However, if the model is too complex, the computational burden will prevent its use on-line in trading departments (Merton, 1976). Cartea and Figueroa (2005), develop a mean-reverting jump diffusion model with seasonality, including mean reversion. An example of an application to electricity prices is given by Jablonska, Viljainen, Partanen and Kauranne (2011). The two main components of all jump-diffusion models are Brownian motion, or the diffusion part, and the Poisson process, or the jump component.

The most basic example of a mean-reverting jump-diffusion model is the one described in Clewlow and Strickland (2000); Clewlow, Strickland and Kaminski, (2001), represented by:

$$dS=\alpha \quad (\mu-\Phi\cdot Km-lnS) \quad S\cdot dt+\sigma\cdot S\cdot dz+K\cdot S\cdot dq \qquad (2.1)$$

where S is the spot price of electricity,
α is the mean-reverting intensity,
μ is the long-run average value of ln(S) in the absence of jumps,
Φ is the average number of jumps per annum,
Km is the mean jump size,
σ is the spot price volatility,
dz is a Wiener process and dq is the Poisson process.

The jump diffusion model takes account of the disturbances implied by the diffusion, with the $\sigma\cdot S\cdot dz$ component, and jumps with (with $K\cdot S\cdot dq$).

A more robust model used for electricity prices is the regime-switching model, which sometimes is also used to represent the merit order regime switching of power plants which enable the activation of costly plants to maintain the system efficiently operating at times of high demand.

This model is based on the transition from one state to a second distinct state governing the underlying process. Autoregressive models with stochastic disturbances are usually used for the representation of mean electricity prices, whereas the simplest specification is that the change in state is the realization of a two-state Markov chain.

More formally, this is expressed as:

$$\Pr(Xn+1=x|X1=x1,2=x2,\ldots,Xn=xn)=\Pr(Xn+1=x|Xn=xn) \qquad (2.2)$$

Where:

The possible values of Xi, or the random variable (the electricity price), are a countable set. Mount, Ning, and Cai, (2006), use regime switching models to predicting electricity price and determinants of electricity prices.

Reduced-form models can be classified as:

- **Spot price models,** this provide a prudent representation of the dynamics of spot prices. Their main problem is the problem of pricing derivative, that is the identification of the risk premium linking spot and forward prices. The two most popular subclasses include jump-diffusion and Markov regime-switching models.
- **Forward price models** allows for the pricing of derivatives in a straightforward approach. However, they too have their limitations most importantly, the lack of data that can be used for calibration and the inability to derive the properties of spot prices from the analysis of forward curves (Guerci, Ivaldi, Cincotti & Silvan, 2008).

2.9.4 Statistical models

Statistical methods forecast the current price by using a mathematical combination of the previous prices and or previous or current values of exogenous factors, typically consumption and production figures, or weather variables (Weron, 2014). The two most important categories are additive and multiplicative models. They differ in whether the predicted price is the sum of a number of components or the product of a number of factors. The former are far more popular, but the two are closely related. A multiplicative model for prices can be transformed into an additive model for log-prices. Statistical models are attractive because some physical interpretation may be attached to their components, thus allowing system operators to understand their behavior. They are often criticized for their limited ability to model the nonlinear behavior of electricity prices and related fundamental variables. However, in practical applications, their performances are not worse than those of the non-linear computational intelligence methods. For instance, in the load forecasting track of the energy competition in 2012 attracting hundreds of participants worldwide, the top four were winning entries used regression models.

Regression type models are based on the theorized relationship between a dependent variable, the electricity price, and a number of exogenous variables which can be estimated. Causal models are similar but include more Granger-based models of causality and cointegration. The exogenous variables to be used in regression models are usually identified using basic fundamental reasoning or according to the correlation they have with the electricity price and both regression and causal models present classic econometric techniques related to regressions. Regressions are usually used in linear forms, though with a stochastic nature employed to describe electricity price volatility. In this study the statistical model was used.

Bollerslev (1986) originally formulated the GARCH (p, q) model as:

$$\sigma t\ _2 = \alpha 0+\alpha_1\varepsilon_t+\cdots+\alpha q\varepsilon_t-q_2+\beta_1\sigma_t\ +\cdots+\beta p\sigma t-p_2 \quad (2.3)$$

This can be summarized as:

$$\sigma t_2 = \alpha_0+\Sigma\ \alpha i\varepsilon_{t-i2}q_i=1+\Sigma\beta_i\sigma t-i_2 pi=1 \quad (2.4)$$

Where:

σt_2 is the variance

ε_{t-i2} is the squared ARCH error.

The lag length p in a GARCH (p, q) process specification shall be found.

In order to do so, we first estimate the best fitting AR(q) model for the mean:

$$Y_t=\alpha_0+\alpha_1 y_{t-1}+\ \cdots\ +\alpha q y t-q+\varepsilon t=\alpha 0+\Sigma\quad =\ 1+\varepsilon t \quad (2.5)$$

To then compute the autocorrelations of the squared error $\varepsilon 2$ through:

$$\rho=\Sigma\ (\hat{\varepsilon t}_2-\hat{\sigma t}2)(\hat{\varepsilon t}-12-\hat{\sigma t}-12)Tt=i+1\Sigma(\hat{\varepsilon t}2-\hat{\sigma t}2)2Tt=1 \quad (2.6)$$

If we consider a large sample, which is usually the case with electricity price intraday data, the asymptotic or standard deviation of (i) is $1/\sqrt{T}$. Values which are larger than $1/\sqrt{T}$ explicitly indicate GARCH errors. In order to estimate the total number of lags, we make use of the Ljung-Box test until the significance of these GARCH errors is less than the usual 5% value. The Ljung-Box Q-statistic follows a Chi-Squared distribution with n degrees of freedom if the residuals are uncorrelated. The null hypothesis assumes no ARCH or GARCH errors. The alternative therefore implies there are GARCH errors within the conditional variance.

Statistical models consist a good class of models, they are:

- Exponential smoothing methods.
- Regression models.
- Time series models.
- Heteroskedastic time series models.

One of the models used in this study is statistical, specifically the regression model.

2.9.5 Computational intelligence models

Computational intelligence techniques combine elements of learning, evolution and fuzziness to create approaches that are capable of adapting to complex dynamic systems, and may be

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regarded as "intelligent" in this sense. Artificial neural networks (Weron, 2014). fuzzy systems and Support Vector Machines (Ruibal & Mazumdar, 2008) are unquestionably the main classes of computational intelligence techniques in EPF. Their major strength is the ability to handle complexity and non-linearity. In general, computational intelligence methods are better at modeling features of electricity prices than the statistical techniques. At the same time, this flexibility is also their major weakness. The ability to adapt to nonlinear, spiky behaviors will not necessarily result in better point or probabilistic forecasts.

2.9.6 Hybrid models

Many of the modeling and price forecasting approaches considered in the literature are hybrid solutions. Their classification is non-trivial, if possible at all. As an example of hybrid model by Alea Model (AleaSoft, 2012) combines Neural Networks and Box Jenkins models.

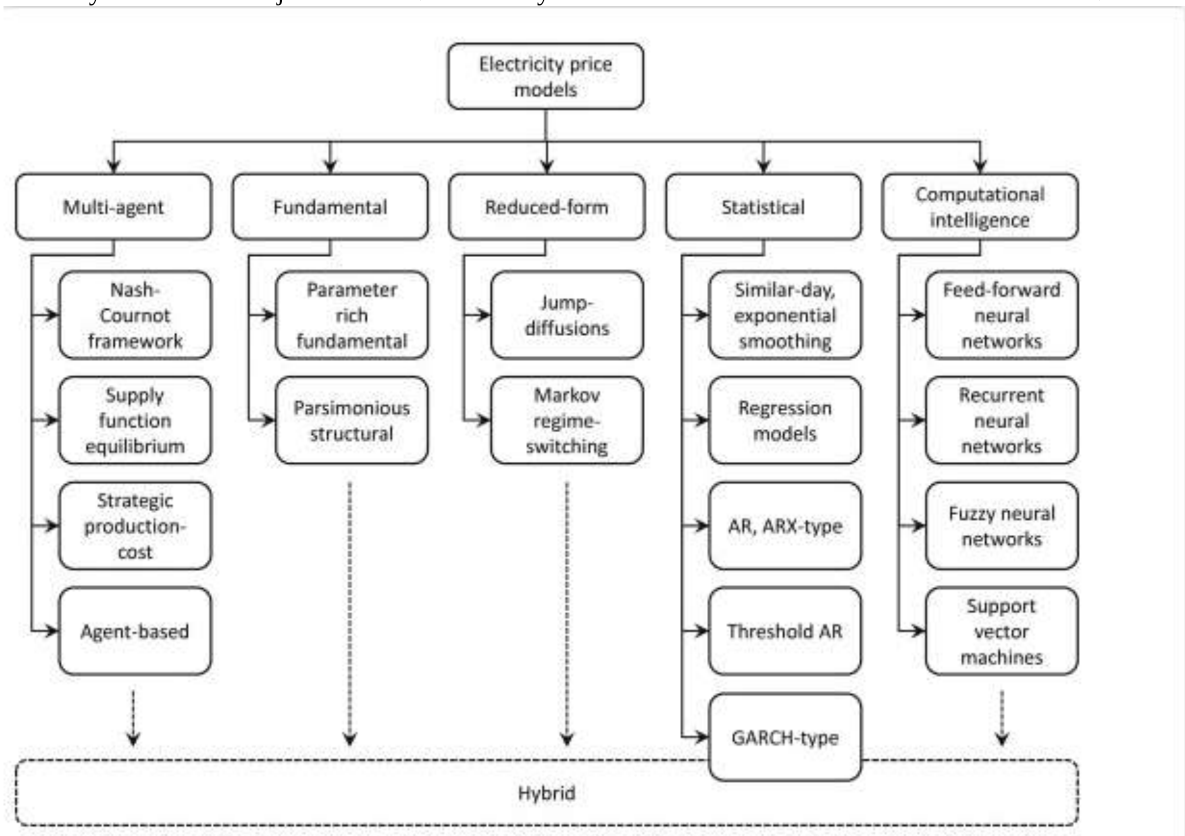

Figure 2.
A taxonomy of electricity spot price modeling approaches. (Weron, 2014).

2.10 Empirical Review

The main models issues and techniques which are related to the forecasting of daily loads and prices in competitive power markets were reviewed by Bun (2000). His conclusion was that forecasting of loads and prices are related activities and that game theory and the economic perspective cannot be “an accurate basis for daily forecasts”. He advocates the use of methods which involve variable segmentation, neural techniques and forecast combinations.

Contreras, Espinola, Nogales and Conejo (2003) in their study predicted the next-day electricity prices of Spain and Californian electricity markets using ARIMA model. Market clearing spot prices of day-ahead pool of Spain and California which were publicly available was used for the study. The authors found inherent differences between the two markets spot price series.

Conejo, Contreras, Espinola and Plazas (2005) in their study compared the forecasting performance of ARIMA model, dynamic regression model and transfer function model by forecasting 24 hour day ahead market-clearing prices of electric energy market. The authors found time series models to be effective than artificial neural network model.

Nogales, Contreras, Conejo and Espinola (2002) in their study provided two specific price forecasting models based on dynamic regression

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model, time series analysis and transfer function models. The authors empirically tested the calibrated models on real world data from the electricity markets of mainland Spain and California. The Average forecast errors for Spanish electricity market was around 5% and the average forecast errors was around 3% for Californian market for the considered time period of study. The authors conclude that price predictions obtained were precise enough to be used by power producers and power consumers for preparing their bidding strategies in competitive power markets of Spain and California.

Weron, Bierbrauer and Truck (2004) in their study forecast day-ahead short-term spot electricity prices of Californian and Nord Pool markets using time series models with an objective of comparing the forecasting accuracy of the calibrated models. For Californian market, 1999-2000 data was considered and for Nord Pool market data of 1998-1999 and 2003-2004 was considered for complete evaluation of models under different scenarios. The results of the study showed that models having system load as exogenous variable in most of the cases out-performed pure price models particularly for California power market.

Furthermore these models seemed to have potential for performing well in-spite of different market conditions.

Shahidehpour, Yamin and Li (2002) discuss the basics of electricity pricing and forecasting, describe a price forecasting model based on neural networks, and comment on performance evaluation. Weron (2006) provides an outline of modeling approach, then focus on practical applications of statistical methods for forecasting price using Autogressive Integrated Moving Average (ARIMA), discuss interval forecasts, and moves on to quantitative stochastic models for derivative pricing (jump-diffusion models and Markov regime-switching). Zareipour (2009) begin by analyzing linear time series models (ARIMA) and nonlinear models (regression, neural networks), with these he forecast prices in the Ontario power market in Canada.

Valle (2002) used ARIMA to forecast inflation in Guatemala. The results showed that ARIMA produced good results and the forecasts behaved according to the underlying assumptions of each model. Okafor and Shaibu (2013) develop a univariate autoregressive integrated moving average (ARIMA) model suggested by Box and Jenkins (1976) for Nigeria inflation and analyze the forecasting performance of the estimated model between 1981 and 2010. In the study, the analyses were carried out with the aid of EViews and Excel software.

Mohammad (2012) posits that price forecasting are done based on different methods including autoregressive integrated moving average (ARIMA), artificial neural network (ANN) and fuzzy regression. The method is examined by using data of Ontario electricity market. The results of different methods are compared and the best method is chosen.

Adepoju, Ogunjuyigbe and Alawode **(**2003) study short-term load forecasting using Artificial Neural Networks (ANNs) and applied it to the Nigeria Electric power system. Historical load data obtained from the Power Holding Company of Nigeria (PHCN, formerly NEPA) for the month of August 2003 were used. An absolute mean error of 2.54% was achieved when the trained network was tested on one week's data. This represents, on average, a high degree of accuracy in the load forecast.

George and Claudia (2004**)** introduce a method for forecasting energy prices using artificial intelligence methods, such as neural networks and fuzzy logic, and a combination of the two. Various factors affecting the market clearing price were investigated.

Weron (2006) provides an overview of modeling approaches, then concentrates on practical applications of statistical methods for day-ahead forecasting, discusses interval forecasts, and moves on to quantitative stochastic models for derivatives pricing (jump-diffusion models and Markov regime-switching).

Amjady and Hemmati (2006) explain the need for short-term price forecasts, review problems related to EPF, and put forward proposals for such predictions. They argue that time series techniques are generally successful in forecasting electricity price.

Weron (2006) investigated the forecasting power of different time series models for electricity spot prices. The models included different specifications of linear autoregressive time series with heteroscedastic noise and or additional fundamental variables. The findings support the adequacy of the tested linear models for forecasting electricity prices, also in comparison to earlier empirical studies.

El-Mefleh and Shotar (2008) applied the Box-Jenkins (ARIMA) methodology to the Qatari economic data. They concluded that ARIMA models were modestly successful in ex-post forecasting for most of the key Qatari economic variables. The forecasting inaccuracy increased the farther away the forecast was from the used data, which is consistent with the expectation of ARIMA models.

Zareipour (2008) reviews linear time series models and nonlinear models (regression, neural networks), then uses them for forecasting hourly prices in the Ontario power market. Aggarwal, Saini, and Kumar (2009) conclude that “there is no hard evidence of out-performance of one model over all other models”. Adebiyi, Adenuga, Abeng, Omamukue and Ononugo (2010) examine the different types of inflation forecasting models covering ARIMA, Vector Autoregressive (VAR), and Vector Error - Correction (VECM) models. The empirical results from ARIMA showed that ARIMA models were modestly successful in explain inflation dynamics in Nigeria.

Aggarwal et al. (2009) also compare ‘time series’ and ‘neural network’ papers. They classify EPF models as falling into one of three categories (although differently from Aggarwal et al., 2009: heuristics (naïve, moving average), simulations (production cost and game theoretical) and statistical models, where the last category somewhat surprisingly includes both time series (regression) and artificial intelligence models. They expand the analysis to include quantitative comparisons of:

- the forecasting accuracy and
- The computational speed of different forecasting techniques. Even if the forecasting accuracy is reported for the same market and the same out-of-sample (forecasting) test period, the errors of the individual methods are not truly comparable if different in-sample (calibration) periods were used.

Pelin and Javier (2011) posit that Long-term price prognosis for electricity is the main tool for making decisions on investments, de-investments as well as on long-term investment and other strategic actions. A number of models are used for analyzing the markets of interest and they are continuously improved and expanded. Their goal was to improve a long-term price prognosis model for France and in order to do this the French hydro system was studied. A hydro model is developed with the help of dynamic programming. The problem is first considered from a deterministic approach where the particular characteristics of the French power system and the relevant assumptions for the model were studied. The model is then expanded with stochastic variables that consider variability of the inflow in the system. Both the deterministic and stochastic model was created using MATLAB. Here, dynamic programming method and the deterministic stochastic methods were used in analyzing the data.

Amjady (2012) briefly reviews EPF methods, and then focuses again on artificial intelligence-based methods, and in particular feature selection techniques and hybrid forecast engines. He also discusses forecast error measures, the fine tuning of model parameters, and price spike predictions.

Amlabu et al (2013) studies a load demand forecasting using least squares technique in four different regional power supplies scenarios in Nigeria. Summarily, the overall result indicated a continuous growth in load demand in the selected regions.

Sergey and Jarmo (2013) propose a forecasting methodology for prediction of both normal prices and price spikes in the day-ahead energy market. The method was based on an iterative strategy implemented as a combination of two modules separately applied for normal price and price spike predictions. The normal price module is a mixture of wavelet transform, linear Auto Regressive Integrated Moving Average (ARIMA) and nonlinear neural network models. The probability of a price spike occurrence is produced by a compound classifier in which three single classification techniques are used jointly to make a decision. Combined with the spike value prediction technique, the output from the price spike model aims to provide a comprehensive price spike forecast. The overall electricity price forecast is formed as combined normal price and price spike forecasts. The forecast accuracy of the proposed method was evaluated with real data from the Finnish Nord Pool Spot day-ahead energy market with ARIMA showing a good result.

Carmona and Coulon (2014) present a detailed analysis of the structural approach for electricity modeling, emphasizing its merits relative to traditional reduced-form models. Building on several recent articles, they advocate a broad and flexible structural framework for spot prices, incorporating demand, capacity and fuel prices in several ways, while calculating closed-form forward prices throughout.

Hong (2014) discusses spatial load forecasting, short-term load forecasting, EPF, and two ‘smart grid era’ research areas: demand-response and renewable-generation forecasting. He classifies EPF models into three groups: simulation methods (which require a mathematical model of the electricity market, load forecasts, outage information, and bids from market participants), statistical methods, and AI methods.

Nitin and Mohanty (2015) studied factors that affect electricity price behavior and established forecasting models based on time series analysis, such as Linear regression based models, they posit that an accurate price forecasting method is an important factor for the market players as it enables them to decide their bidding strategy to maximize profits.

2.11 Theoretical Framework

Numerous methods have been developed for electricity price forecasting and most of these algorithms are same as used for forecasting. The price-forecasting theories have been classified in three sets Gonzalez, San, and Garcia (2005).

2.11.1 Game Theory Models

Game theory is a branch of applied mathematics that provides tools for analyzing situations in which parties, called players, make decisions that are interdependent. This interdependence causes each player to consider the other player's possible decisions, or strategies, in formulating his own strategy. The first group of models is based on game theory. It is of great interest to model the strategies (or gaming) of the market participants and identify solution of those games. Since participants in oligopolistic electricity markets shift their bidding curves from their actual marginal costs in order to maximize their profits, these models involve the mathematical solution of these games and price evolution can be considered as the outcome of a power transaction game. In this group of models, equilibrium models take the analysis of strategic market equilibrium as a key point Bajpai (2004).

2.11.2 Simulation Models

These models form the second class of price forecasting techniques, where an exact model of the system is built, and the solution is found using algorithms that consider the physical phenomenon that governs the process. Then, based on the model and the procedure, the simulation method establishes mathematical models and solves them for price forecasting. Price forecasting by simulation methods mimics the actual dispatch with system operating requirements and constraints. It intends to solve a security constrained optimal power flow (SCOPF) with the entire system range Bastian, Zhu, Banunaryanan, and Mukherji (1999)

Time series analysis is a method of forecasting which focuses on the past behavior of the dependent variable Box, Jenkins, and Reinsel (2004). Sometimes exogenous variables can also be included within a time series framework. Based on time series, there are further three types of models.

2.11.3 Parsimonious Stochastic Models

According to Bunn and Karakatsani (2003), many stochastic models are inspired by the financial literature and widely applied in practice. Univariate discrete type models like autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and generalized autoregressive conditional heteroskedastic (GARCH) are models that have been considered. This work is based on parsimonious stochastic model.

Stochastic time series can be divided into stationary process and non-stationary process. The basic assumption of stationarity on the error terms includes zero mean and constant variance. In AR, MA and ARMA models conditions of stationarity are satisfied; therefore they are applicable only to stationary series. ARIMA model tries to capture the incremental evolution in the price instead of the price value. By the use of a different operator, transformation of a non-stationary process into a stationary process is performed. The class of models where the constant variance assumption does not need to hold is named heteroskedastic. Thus, GARCH model considers the conditional variance as time dependent. In all these models, price is expressed in terms of its history and a white noise process. If other variables are affecting the value of price, the effect of these variables can be accounted for using multivariate models like TF (transfer function) and ARMA with exogenous variables (ARMAX) models. As electricity price is a non-stationary process, which exhibits daily, weekly, yearly and other periodicities. Therefore, a different class of models that have this property, designated as seasonal process model, is used.
According to Moghram and Rahman (1989). The available NN models are:

(i) multilayer feed forward NN (FFNN)
(ii) radial basis function network (RBF)
(iii) support vector machine (SVM)
(iv) self-organizing map (SOM)
(v) committee machine of NNs and
(vi) recurrent neural network (RNN).

2.12 Methodological Framework

Granger Causality Analysis

Granger causality describes the dependency relationships between two time series. This section introduces the Granger (1969) test, explaining the econometric details relevant to the type of data under analysis. Granger-causality was initially proposed in the context of econometrics to enable the investigation of causal influence between two series.

According to Karagianni, Pempetzoglou, and Saraidaris (2009), according to this test, if two distinct series $\{Xt, \geq 1\}$ are strictly stationary, $\{Yt\}$ Granger-causes $\{Xt\}$ if past and current values of Y embody further information regarding the future values of X. In fact, supposing that FX,t and FY,t denote the relevant information set of past values of both Xt and Yt, at time t, {Yt} is said to Granger-cause {Xt} if the following condition is satisfied:

$(Yt+1,\ldots,+k) \mid (FX,t,FY,t) \sim (Yt+1,\ldots,Yt+k) \mid FX,t$ (2.7)

Where '~' denotes distribution equivalence.
Supposing that:

$XtlX = (Xt-\ell X+1\ldots Xt)$ (2.8)

and that

$YtlY = (Yt-\ell Y+1,\ldots, Yt)$ (2.9)

represent the lag-vectors,
where ℓX, ℓY ≥ 1, the null-hypothesis states that realized values of $XtlX$ embed further evidence on Yt + 1, beyond that present in$YtlY$. The null is then expressed as follows:

$$H_0 = Y_{t+1} \left| \left(X_t^{l_x}; Y_t^{l_y} \right) \sim Y_{t+1} \right| Y_t^{l_y}$$

(2.10)

Thereby stating that the prediction of the one period future value of Y given the combined information set of X and Y is the same as the same prediction made with only the information set, or time series, of Y alone. The relative test statistic is formulated as:

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \cdot \sum_i \{\hat{f}_{X,Z,Y}(X_i, Z_i, Y_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i Y_i)\hat{f}_{Y,Z}(Y_i, Z_i)\}.$$

2.11

For ℓX = ℓY = 1
and in the case that:

$\varepsilon n = Cn - (C>0, 1/4<\beta<1/3)$

(2.12)

Diks and Panchenko (2006) provide evidence that the test-statistic satisfies the following equation (Karagianni et al., 2009).

$$\sqrt{n}\frac{T_n(\varepsilon_n - q)}{S_n} \xrightarrow{D} \mathrm{N}(0,1)$$

(2.13)

where $D\rightarrow$ denotes the statistic convergence to a normal distribution and where Sn represents the estimator of the asymptotic variance relative to Tn(·). Thus, in accordance with the latter, a single-tailed test form was used.

Previous studies have used Granger-causality to analyse the causal relationship between stock prices and exchange rates Granger et al., 1998. Woo, Horowitz and Luk (2006) represent one of the very few studies to use electricity prices and causality testing, using the Granger instantaneous-causality test to explore the potential causal relationships between wholesale electricity prices and natural gas prices in California. Similarly, (Ferkingstad, Lølanda, & Wilhelmsen, 2011) apply causal inference to determine the relationship between fuel, gas, coal on electricity prices.

Autoregressive Moving Average

A time series is defined as a sequence of data observed over time. ARIMA models are a class of models that have capabilities to represent stationary as well as non-stationary time series and to produce accurate forecasts based on a description of historical data of single variable. The Box-Jenkins (1976) methodology refers to the set of procedure for identifying, fitting, and checking autoregressive integrated moving average (ARIMA) models with time series data (Hanke & Wichern, 2005; Roberts, 2006). Forecasts follow directly from the form of the fitted model. ARIMA methodology is not embedded within any underlying economic theory or structural relationship, and the forecasts from the models are based purely on the past behaviour and previous error terms of the series of interest (Hanke & Wichern, 2006).

The Box-Jenkins (ARIMA) econometric modeling is a forecasting technique that completely ignores independent variables in making forecast. It takes into account historical data and decomposes it into Autoregressive (AR) process, where there is a memory of past events; an Integrated (I) process, which accounts for stabilizing or making the data stationary, making it easier to forecast and a Moving Average (MA) of the forecast errors, such that the longer the historical data, the more accurate the forecasts will be, as it learns over time. ARIMA models therefore have three model parameters, one

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for the AR(p) process, one for the I(d) process, and one for the MA(q) process, all combined and interacting among each other and recomposed into the ARIMA (p, d, q) model. The ARIMA models are applicable only to a stationary data series, where the mean, the variance, and the autocorrelation function remain constant through time. The only kind of non-stationarity supported by ARIMA model is simple differencing of degree d. In practice, one or two levels of differencing are often enough to reduce a non-stationary time series to apparent stationarity (Hanke & Wichern, 2005; Roberts, 2006).

Any forecasting technique that ignores independent variables also essentially ignores all potential underlying theories except those that hypothesize repeating patterns in the variable under study. Since the advantages of developing theoretical underpinnings of a particular equation before estimating them have been emphasized in regression theory, why would we advocate ARIMA? The answer is that the use of ARIMA is appropriate when little or nothing is known about the dependent variable being forecasted or when all that is needed is one or two-period forecast (Hanke & Wichern, 2005; Roberts, 2006). In these cases, ARIMA has the potential to provide forecasts that are superior to more theoretically satisfying regression models. The approach of Box-Jenkins methodology in order to build ARIMA models is based on the following steps:

(1) Model Identification,
(2) Parameter Estimation and Selection,
(3) Diagnostic Checking (or Modal Validation); and
(4) Model's use.

Model identification involves determining the orders (p, d, and q) of the AR and MA components of the model. Basically, it seeks the answers for whether data is stationary or non-stationary. What is the order of differentiation (d), which makes the time stationary? The ARIMA model cannot be built until we make this series stationary. We first have to difference the time series‘d’ times to obtain a stationary series in order to have an ARIMA (p, d, q) model with ‘d’ as the order of differencing used. We must be cautious in differencing as over differencing will tend to increase in the standard deviation, rather than a reduction. The best idea is to start with differencing with lowest order (of first order, d=1) and test the data for unit root problems. ARIMA model types are listed using standard notation of ARIMA (p, d, q) and (P, D, Q) are their seasonal counterparts.

Autoregressive (p): the number of autoregressive orders in the model. Autoregressive orders specify which previous values from the series are used to predict current values.

Difference (d): specifies the order of differencing applied to the series before estimating models. Differencing is necessary when trends are present (series with trends are typically non stationary).

2.13 Gaps in Literature

After extensive review of the literature, we observed the following gaps in the literature:

1) There is a need to study the emergence of competitive deregulated electricity market in Nigeria.
2) There is a need to study the dynamics, behavior and impact of some economic factors such as inflation, interest rates, exchange rates, and technical factor like fuel price, on Port Harcourt electricity prices.
3) There is a need to empirically model and forecast Port Harcourt electricity prices, which to the best of my knowledge, has never been done before.
4) There is a need to empirically investigate Autoregressive Integrated Moving Average (ARIMA) and with regression model to model electricity prices.

III. CHAPTER THREE
METHODOLOGY

3.1 Introduction

This chapter presents a careful description of the research design, model specification, sources of data, estimation techniques, justification of methodology, forecast performance measures, stationarity testing and the limitation of methodology to ensure that the results of the research are dependable, accurate and valid.

3.2 Research Design

The research design is a long term study of electricity price forecasting for Port Harcourt Distribution Company. The study considers a 9-year period series of measuring time series data that cover the period from 2008 to 2016. The choice of the sample period is dictated by the desire to take a long-term view of electricity price forecast in the Distribution Company. The research design adopted in this study was the ex- post facto research design. The reason is that the variables under consideration are historical in nature.

3.3. Population and Sample of the Study

All the customers' classes and the distribution Companies in Nigeria serves as the population of this study. Electricity price of C3 (maximum Demand) of the commercial class of

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Port-Harcourt electricity distribution Company was considered as the sample of the study.

3.4 Model Specification

A model is therefore developed from Granger causality theory (1969) and adapted from the work of Ferkingstad et al., (2011) to test the potential causal relationship between electricity price and inflation rate, exchange rate, interest rate and cost of fuel. Causal forecasting suggests that we can forecast electricity price using variables that seem to influence it. This is technically called regression modeling (Sean, 2013; Weron, 2014). The model for this study is hereby specified thus:

$$EPF_t = \alpha_t + \beta_1 Inf_t + \beta_2 E_t + \beta_3 Int_t + \beta_4 F_t + \epsilon_t \quad (3.1)$$

Where:
t= 2008-2016
EPF_t = Electricity Price;
Inf = Inflation rates;
E = Exchange Rate;
Int = Interest Rate;
F = Fuel cost;
α = intercept;
β = slope coefficient and
ε= the error term.
β_i's> 0

Using the yearly average, we include inflation rate as a potential relevant regressor. The direction this variable will play is difficult to say in advance. On the other hand, the inflation variable is not expected to be positively related to price of electricity since the rate of inflation is used to ensure that investors are well compensated against rising cost of doing business and workers in the industry are paid living wages.

Also, we expect a nonlinear relationship between fuel cost and price of electricity. Fuel is what drives the turbine to produce electrical energy. Besides, exchange rates are expected to be positively related to electricity price, Nigeria being an importer of electricity generation equipment components opens Nigeria to foreign exchange risk. Finally, interest rate is expected to be inversely related to electricity price as Nigeria Electricity Regulatory Commission has regard to relevant yields on Nigeria Treasury bonds.

Arima Model Development

A pth –order autoregressive process expresses a dependent variable as a function of past values of the dependent variable, as in:

$$Y_t = \varnothing_o + \varnothing_1 Y_{t-1} + \varnothing_2 Y_{t-2} + . . . + \varnothing_p Y_{t-p} + \varepsilon_t \quad (3.2)$$

Where:
Y_t is the response (dependent) variable being forecasted at time t.
$Y_{t-1}, Y_{t-2}, . . . Y_{t-p}$ is the response variable at time lags t - 1, t-2, . . . t – p, respectively.
$\varnothing_1, \varnothing_2, . . . , \varnothing_p$ are the coefficient to be estimated.
ε_t is the error term at time t.

This equation is similar to the serial correlation error term and to the distributed lag equation. Since there are p different lagged values of Y in the equation, it is often referred to as a 'pth-order" autoregressive process. More generally, the function can be written as:

A qth-order moving – average process which expresses a dependent variable Y_t as a function of the past values of the q error terms, as in:

$$Y_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + . . . + \theta_q \varepsilon_{t-q} \quad (3.3)$$

Where:
Y_t is the response (dependent) variable being forecasted at time t.
μ is the constant mean of the process.
$\theta_1, \theta_2, . . . , \theta_p$ are the coefficient to be estimated.
ε_t is the error term at time t.
$\varepsilon_{t-1}, \varepsilon_{t-2}, . . . , \varepsilon_{t-q}$ are the error terms in previous time periods that are incorporated in the response Y_t.

Such a function is a moving average of the past error terms that can be added to the mean of Y to obtain a moving average of past values of Y. Such an equation would be a 'qth-order' moving-average process.

To create an ARIMA model, we begin with an econometric with no independent variables ($Y_t = \beta_o + \varepsilon_t$) and added to it both the autoregressive (AR) process and the moving-average (MA) process.

Autoregressive process

Moving Average process

$$Y_t = \beta_o + \varnothing_1 Y_{t-1} + \varnothing_2 Y_{t-2} + . . . + \varnothing_p Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + . . . + \theta_q \varepsilon_{t-q} \quad (3.4)$$

Where the Øs and the θs are the coefficients of the autoregressive and the moving – average processes, respectively.

Following Box and Jenkins (1976), an autoregressive moving average (ARIMA) model may be specified as thus:

$$EPC_t = \beta_o + \varnothing_1 EPC_{t-1} + \varnothing_2 EPC_{t-2} + . . . + \varnothing_p EPC_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + . . . + \theta_q \varepsilon_{t-q} \quad (3.5)$$

Where:
EPC_t is the electricity Price for Commercial series and β_o, Ø, and θ are the parameters to be estimated.

Before this equation can be applied to a time series, however, it must be assumed that series is stationary. If a time series is non-stationary, then steps must be taken to convert the series into a stationary one before ARIMA can be applied. For

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example, a non stationary series can often be converted into a stationary one by taking the first difference of the variable in question.

$EPC^*t = \Delta EPC_t = EPC_t - EPC_{t-1}$ (3.6)

If the first difference does not produce a stationary series then first differences of this first-differenced series can be taken. The resulting series is a second- difference transformation:

$EPC_t^{**} = (\Delta EPC_t^*) = EPC_t^* - EPC_{t-1}^* = \Delta EPC_t - \Delta EPC_{t-1}$ (3.7)

In general, successive differences are taken until the series is stationary. The number of differences required to be taken before a series becomes stationary is denoted with the letter d. In practice, d is rarely more two (2) (Makridakis, Wheelwright, & Hyndman, 1998) as cited in (Okafor & Shaibu, 2013)

The dependent variable in equation 4 must be stationary, so the EPC in that equation may be EPC, EPC*, or even EPC**, depending on the variable in question. If a forecast of EPC* or EPC** is made, then it must be converted back into EPC terms before its use.

This conversion process is similar to integration in mathematics, so the "I" in ARIMA stands for 'integrated" ARIMA stands for **A**utogressive **I**ntegrated **M**oving **A**verage. If the original series is stationary and d therefore equals o, this is shortened to ARMA.

As a shorthand, an ARIMA model with the p, d, q specified is usually denoted as ARIMA (p, d, q) with the specified integers chosen inserted for p, d, and q as in ARIMA (2, 1, 1) would indicate a model with two autoregressive terms, one difference, and one moving average term.

ARIMA (2, 1, 1): $Y_t^* = \beta_o + \theta_1 Y_{t-1}^* + \theta_2 Y_{t-2}^* + \varepsilon_t + Ø_1 \varepsilon_{t-1}$

Where: $EPC_t^* = \Delta EPC_t = EPC_t - EPC_{t-1}$ (3.8)

Forecasts are often more useful if they are accompanied by a confidence interval, which is a range within which actual value of the independent variable is expected to lie. This is given as:

$\grave{E}PC_{T+1} \pm S_F t$

(3.9)

Where S_F is the estimated Standard Error of the forecast and t_c is the critical two – tailed t- value for the desired level of significance.

ARIMA approach will be used to understand the trend and prediction of future electricity price in Port Harcourt Distribution Company. The independent variables are inflation rates, interest rate, exchange rate and cost of fuel.

3.5 Sources of Data

Electricity price data was sourced from records of the Nigerian Electricity Regulatory Commission, Port-Harcourt Distribution Company. The commission is agency in charge of establishment and development of a new tariff regime based on industry revenue requirements for the company. These sourced data contains electricity prices according to customer classification. The data on inflation rate, interest rate and exchange rate were sourced from Central Bank of Nigeria, while data on fuel cost from Nigeria National Petroleum Corporation. The selection of data and explanatory variables for the model is based on data availability.

3.6 Estimation Techniques

Based on the objectives of the study, the data were analyzed using ARIMA model and Ordinary Least Square (OLS). Considering the stability of the result, we estimated the log linear regression model using Ordinary Least Square (OLS). In addition, a battery of test was carried out, such as test for serial correlation, unit root test, Durbin Watson statistic, Jacque Bera to test for normality of the error term. This was performed using E-view and Excel software. The log linear regression model determined the significant predictors of electricity price in Port Harcourt Distribution Company using a regression equation obtained from inflation rate, exchange rate, interest rate and cost of fuel. The inclusion of log linear regression model is predicated on the need to identify the major determinants or predictors of electricity at the ninety five percent confidence level as well as utilize the model to forecast electricity price in Port Harcourt Distribution Company.

3.7 Justification of Methodology

ARIMA models have proven themselves to be relatively robust especially when generating forecasts. ARIMA models frequently outperform more sophisticated structural models in terms of short-run forecasting ability Stockton and Glassman (1987) and Litterman (1986). Therefore, the ARIMA forecasting technique outlined in this paper will not only provide a benchmark by which other forecasting techniques may be appraised, but will also provide an input into forecasting in its own right. It is assumed that past values of the series plus previous error terms contain information for the purposes of forecasting. The main advantage of ARIMA forecasting is that it requires data on the time series in question only.

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It avoids a problem that occurs sometimes with multivariate models. For example, consider a model including wages, prices and money. It is possible that a consistent money series is only available for a shorter period of time than the other two series, restricting the time period over which the model can be estimated.

3.8 Forecast Performance Measures

Forecasting measurement of the two models used in this study is based on Mean Square Error (MSE). MSE is a relative measurement used for comparison across the testing data because it is easy to interpret, independent of scale, reliable and valid (Feridun & Adebiyi, 2006; Chang, 2007). The MSE has been said to be asymmetric in that it treats over estimations and under estimations differently (Goodwin & Lawton, 1999). However, it remains one of the most widely used and reliable measures of forecast performance and so we used it here (Willmain, 1991; Law, 2000: Meade, 2000). On the basis of these aforementioned selection and evaluation, concluding remarks were drawn.

Also, the forecasting performance of ARIMA model and regression model was examined by calculating Akaike Information Criterion to select the best fit model for future forecasting. The normalized correlation coefficient (R) was used to measure the closeness of the observed and estimated data and the goodness of fit was compared with the coefficient of Determination (R^2).

3.9 Testing For Stationarity

The time series under consideration must be stationary before one can attempt to identify a suitable ARIMA model. A large literature has developed in recent years on the issue of testing time series for stationarity and non-stationarity Harris (1995), Banerjee et al (1993).

For AR or ARMA models to be stationary it is necessary that the modulus of the roots of the AR polynomial be greater than unity, and for the MA part to be invertible, it is also necessary that the roots of the MA polynomial lie outside the unit circle. Theoretically, Box-Jenkins model identification is relatively easy if one has a pure AR or a pure MA process. Stationarity here was achieved after the first difference.

Having determined the correct order of differencing required rendering the series stationary, the next step is to find an appropriate ARIMA form to model the stationary series. The traditional method utilises the Box-Jenkins procedure, in which an iterative process of model identification, model estimation and model evaluation is followed. The Box-Jenkins procedure is a quasi-formal approach with model identification relying on subjective assessment of plots of autocorrelograms and partial autocorrelograms of the series. Objective measurement of model suitability, in particular traditional Box-Jenkins procedure was used. The Box-Jenkins methodology essentially involves examining plots of the sample autocorrelogram, partial autocorrelogram and inverse autocorrelogram and inferring from patterns observed in these functions the correct form of ARIMA model. The Box-Jenkins methodology is not only about model identification but is, in fact, an iterative approach incorporating model estimation and diagnostic checking in addition to model identification Gómez and Maravall (1998).

3.10 Limitation of Methodology

One common pitfall of ARIMA modeling is to over fit the model at the identification stage, which maximizes the in-sample explanatory performance of the model but may lead to poor out-of-sample predictive power relative to a more parsimonious model. Some other disadvantages of ARIMA forecasting are that:

Some of the traditional model identification techniques are subjective and the reliability of the chosen model can depend on the skill and experience of the forecaster (although this criticism often applies to other modeling approaches as well). It is not embedded within any underlying theoretical model or structural relationships.

Furthermore, it is not possible to run policy simulations with ARIMA models, unlike with structural models. ARIMA models are essentially backward looking. As such, they are generally poor at predicting turning points, unless the turning point represents a return to a long-run equilibrium.

IV. CHAPTER FOUR

DATA PRESENTATION AND ANALYSIS

4.1 Introduction

Generally, this chapter empirically reveals the ARIMA model and regression models developed and specified in chapter 3. The annual data of electricity price, inflation rate, interest rate, exchange rate and cost of fuel. These data were sourced from the publication of the NNPC and National bureau of statistics (NBS). The study used the Autoregressive Integrated Moving Average and Regression model to analyze electricity price over the specified period. The analysis was done with the aid of Eviews software and Excel software. The

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study used the Ordinary Least Square (OLS) technique for estimation purposes.
This chapter focuses on identifying ARIMA and Regression models that would be relevant in analyzing electricity price in Port-Harcourt. Since previous studies have been carried out in other countries using ARIMA and regression models.

The remaining part of this chapter is organized as follows. Section 4.2 provides data examination. Section 4.3 provides model estimation and interpretation.

4.2 Data Examination

It is very important to check or look into the structure of the data to be used so as obtain a preliminary knowledge about the stationarity of the data.

4.2.1 Time Series Analysis

Before performing formal tests, the graphs of the time series under study were plotted. Such plots give initial clue about the likely nature of the time series. The figures below show the line graph of the historical performance of Electricity Price for Commercial Class (EPC) series of Port Harcourt Distribution Company used in this study.

Figure 1 below shows the graph of the series at their level form while Figure 2 shows the graphs of the logarithmic values of the series.

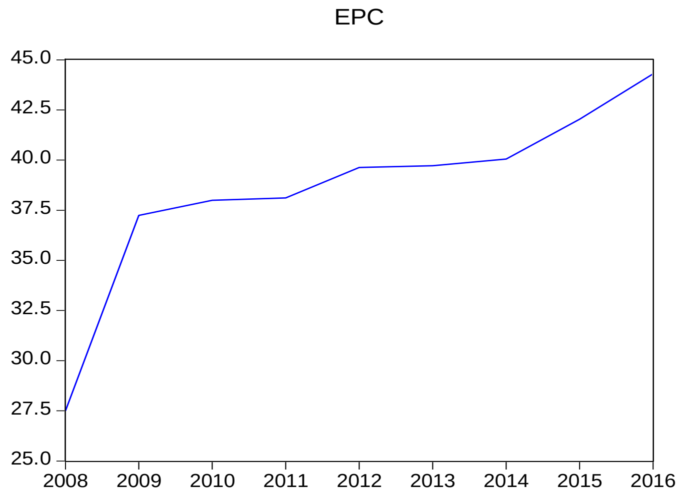

Figure 1: Variables at Levels

Source: Authors' Calculations.

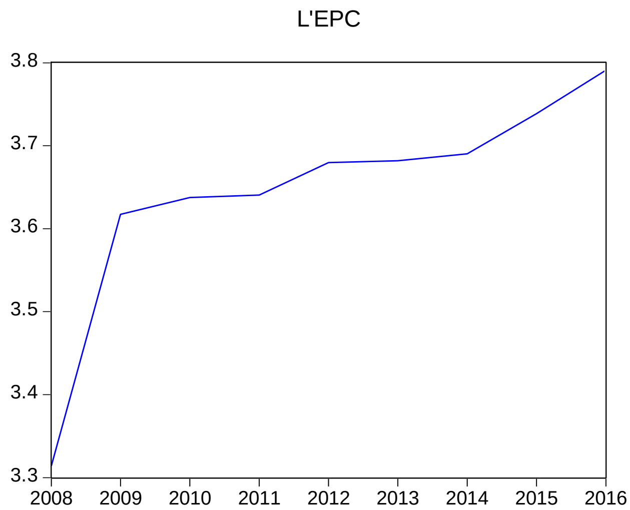

Figure 2: Logarithm of Variables

Source: Authors' Calculations.

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Figures 1 and 2 show that there is little evidence to suspect the presence of structural break or outlier in the five variables. However, the graphs reveal that constructing a model for the logarithmic values is likely to be more advantageous because the changes in the logarithmic series display a more stable variance than the changes in the original series. The logarithmic transformation helps to stabilize the variance of the series.

4.2.2 Descriptive Statistics

The table below provides a full descriptive statistics of the macroeconomic variables used for the research models. The table shows the mean, standard deviation, skewness, kurtosis and normality of the variables. The study variables include: Inflation rate, interest rate, exchange rate and fuel cost index. The table below shows the mean, standard deviation, skewness and kurtosis of the research variables. These statistics are discussed below.

Table 1: Mean, Standard Deviation, Skewness and Kurtosis of the research Variables

DESCRIPTIVE STATISTICS

	EPC	INF	INT	EXCH	FC
Mean	3.643423	2.438228	2.018582	5.154388	4.512987
Median	3.679586	2.564949	2.127041	5.068904	4.540098
Maximum	3.790985	2.753661	2.403335	5.717028	4.973971
Minimum	3.314186	2.091864	1.252763	4.927254	4.120662
Std. Dev.	0.134593	0.233098	0.366746	0.236521	0.308290
Skewness	-1.708800	-0.442593	-1.094385	1.623793	0.011196
Kurtosis	5.277442	1.744151	3.134052	4.675619	1.691577
Jarque-Bera	6.325025	0.885266	1.803255	5.007945	0.642177
Probability	0.042319	0.642343	0.405908	0.081760	0.725359
Sum	32.79081	21.94405	18.16724	46.38949	40.61688
Sum Sq. Dev.	0.144921	0.434677	1.076019	0.447537	0.760344

Source: EViews Output, 2017.

Electricity Price for Commercial Class: the number of observations used for computing this statistics is 9. The minimum value is 3.3142, maximum value is 3.7910, mean is 3.6434, standard deviation is 0.1346, skewness is -1.7088 while kurtosis is 5.2774.

Inflation Rate: the number of observation used for computing this statistics is 9. The minimum value is 2.0919, maximum value is 2.7537, mean is 2.4382, standard deviation is 0.2331, skewness is -0.4426, while kurtosis is 1.7442.

Interest Rate: the number of observations used for computing this statistics is 9. The minimum value is 1.2528, maximum value is 2.4033, mean is 2.0186, standard deviation is 0.3667, skewness is -1.0944 while kurtosis is 3.1341.

Exchange Rate: the number of observations used for computing this statistics is 9. The minimum value is 4.9273, maximum value is 5.7170, mean is 5.1544, standard deviation is 0.2366 skewness is 1.6238 while kurtosis is 4.6756

Fuel Cost: the number of observations used for computing this statistics is 9. The minimum value is 4.1207, maximum value is 4.9740, mean is 4.5130, standard deviation is 0.3083, skewness is 0.0112 while kurtosis is 1.6916.

4.2.3Unit Root Test for the EPC Series

A stationary series must be obtained before it can be used to specify and estimate a model. The unit roots test will help us to determine the stationarity of a series. The Augmented Dickey-Fuller (ADF) is used to test for the stationarity of the EPC series. The test results for the time series variable are presented in Table 1 below.

Table 2: Results of Unit Root Test

Variable	ADF Test Statistic	95% Critical ADF Value	Remark
D(LEPC)	-1.427	-1.964	Non-Stationary
D(LEPC,2)	-4.803**	-1.964	Stationary
Note: ** = significant at 5percent.			

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Source: Authors' Calculations**.**

In the results shown above, the ADF test statistic for the variable (-4.803) is greater than the respective 95 percent critical values (-1.964). In the final evaluation the price of Electricity (EPC) became stationary at first difference.

4.3 Model Estimation and Interpretation

The objective of this study was to analyze the EPC series with ARIMA model. ARIMA models are univariate models that consist of an autoregressive polynomial, an order of integration (d), and a moving average polynomial. Since the logarithm of EPC became stationary after first order difference (ADF test) the model that we are looking at is ARIMA (p, 1, q). We have to identify the model, estimate suitable parameters, perform diagnostics for residuals and finally forecast the EPC series. The following procedure was followed in estimating the univariate autoregressive integrated moving average (ARIMA) model that was specified. First, EPC series variable was transformed to stabilize the variable. Second, potential models were identified using the autocorrelation function (ACF) and the partial autocorrelation function (PACF) and estimated via Ordinary Least Squares (OLS) method. Third, the best model is selected using the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC). Fourth, the selected model was estimated and diagnostic tests of residuals were performed. Finally, the estimated model was used to forecast the price of electricity.

4.3.1 Model I: Model Identification (ARIMA)

Firstly, we computed the series correlogram which consists of ACF and PACF values as in Figure 1.3. We also calculated the Ljung-Box Q-statistics. We observed the patterns of the ACF and PACF, and then determine the parameter values p and q for ARIMA model. The correlogram for ACF and PACF of the first order difference series was plotted in Figure 3.
Correlogram of D (LEPC, 2) Residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |* . |	. |* . |	1	0.209	0.209	0.5415	0.462
. | . |	. | . |	2	0.096	0.055	0.6718	0.715
. |* . |	. **| . |	3	0.061	0.032	0.7324	0.866
. | . |	. | . |	4	-0.056	-0.083	0.7946	0.939
. *| . |	. *| . |	5	-0.103	-0.086	1.0548	0.958
. *| . |	. *| . |	6	-0.129	-0.091	1.6053	0.952
. **| . |	. *| . |	7	-0.243	-0.195	4.5232	0.718
. **| . |	. **| . |	8	-0.335	-0.266	15.649	0.048

Figure 3: Correlogram of the first order difference LEPC series
Source: Authors' Calculations**.**

In Figure 3 above, 8 lags of autocorrelation and partial autocorrelation were generated. The ACF died out after lag 2(AR) and PACF died out slowly after lag 4(MA). Thus, the p and q values for the ARIMA (p, 1, q) model were set at 2 and 4 respectively. So, we temporarily set our ARIMA model to be ARIMA (2, 1, 4). From the correlogram of the first order differenced series, it seems an AR (1), or AR (2) might be adequate, while MA(1), MA(2), MA(3) or MA(4) might also be adequate. This therefore suggests the possibility of the following combinations of ARIMA: ARIMA(1,1,1), ARIMA(1,1,2), ARIMA(2,1,3) and ARIMA(2,1,4). From these possible ARIMA combinations, the AIC and SIC criteria were used to select the most desirable ARIMA model. The results of all the ARIMA combinations are presented in Table below.

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Table 3: ARIMA Models for Electricity Price Forecasting

Variable	ARIMA(1,1,1)	ARIMA(1,1,2)	ARIMA(2,1,3)	ARIMA(2,1,4)
C	0.0065 (0.0035)	0.1157 (0.000)	0.0007 (0.035)	-0.092 (0.105)
AR(1)	0.225 (0.005)	0.0385 (0.004)	-0.0125 (0.029)	0.287 (0.005)
AR(2)			0.0122 (0.43)	0.468 (0.0225)
MA(1)	0.165 (0.004)	-0.077 (0.032)	0.089 (0.000)	0.0145 (0.000)
MA(2)		0.0065 (0.0045)	0.095 (0.045)	0.088 (0.001)
MA(3)			0.0065 (0.045)	-0.075 (0.027)
MA(4)				-0.0065 (0.000)
R^2	0.42	0.44	0.45	0.43
Adjusted R^2	0.41	0.43	0.44	0.42
Durbin-Watson	1.15	1.28	1.33	1.35
Akaike Information Criterion	-2.65	-2.63	-2.63	-2.64
Schwarz Information Criterion	-2.65	-2.64	-2.59	-2.66
Root Mean Square Error	0.054	0.056	0.056	0.057
TIC	0.91	0.92	0.93	0.89

Source: Authors' Calculations**.**

In selecting the best ARIMA model of EPC series, we subjected all the ARIMA models to Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). The results above show that ARIMA (2, 1, 3) is preferred to others since it has the lowest values of AIC and SIC.

4.3.2 ARIMA (2, 1, 3) Estimation and Interpretation

When we have identified the ARIMA model, the next step was to estimate the parameter coefficients. The parameter estimation of the model was conducted using the EViews software. Table 4 tabulates the results

Table 4: The Parsimonious ARIMA (2, 1, 3) Result

Dependent Variable: D (LEPC, 2)

Variable	Coefficient	t-Statistic	Prob.
C	0.0007	0.8578	0.035
AR(1)	-0.0125	-0.6734	0.029
AR(2)	0.0122	-5.965	0.43
MA(1)	0.089	0.0058	0.000
MA(2)	0.095	0.3589	0.045
MA(3)	0.0065	0.0007	0.045
R-squared	0.4543		
Adjusted R-squared	0.4441		

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F-statistics	15.833		
Durbin-Watson stat	1.33		
Inverted AR Roots	-0.00+0.78i	-0.00-0.78i	
Inverted MA Roots	0.58	-0.01+0.98i	-0.01-0.98i

In Table 4, ARIMA (2, 1, 3) results indicate that the coefficients of AR (2), and MA (3) were highly significant at 5% levels. The AIC (-2.63) and SIC (-2.59) were lower in values when compared to ARIMA(1,1,1), ARIMA(1,1,2), (2,1,3) and (2,1,4). The adjusted R-squared of ARIMA (2,1,3) which is 0.45 (45) was also higher when compared to other ARIMA models indicating that ARIMA (2,1,3) goodness of fit for forecasting is preferred to other ARIMA models.

From the t-statistics for the coefficient variables AR (p) and MA (q) in Table 4, the null hypothesis that the coefficients are equal to zero is rejected. The value for R-squared was 0.45 which implies that about 45% of the variation in EPC in Port Harcourt is explained by past values of EPC and the past errors. The D-W statistic of 1.33 showed that there was little or no evidence to accept the presence of serial correlation in the model. Thus, the model equation can be formed as:

$$\Delta(LEPC_{t,1}) = 0.0007\text{-}0.0125_{t-1}+0.0122_{t-2}+0.089_{t-1}+0.095_{t-2}+0.0065_{t-3} \quad (4.2)$$

(0.035) (0.029) (0430) (0.000) (0.045) (0.045)

The results showed that the coefficient of EPC expectation was positively significant both in the first quarter lag and in the second quarter lag. This is consistent with the theoretical expectation.

4.3.3 ARIMA (2, 1, 3) Diagnostic Tests

After estimating the parameters for ARIMA (2, 1, 3) model, it was also necessary to examine the statistical properties of the estimated ARIMA model in checking the model adequacy. The ARIMA (2, 1, 3) was tested for specification error, serial correlation, and heteroskedasticity.

Table 5: ARIMA (2, 1, 3) DIAGNOSTIC TEST

TEST	F-STATISTIC	P-VALUE
Specification Error: Ramsey RESET test	0.7433	0.327
Serial correlation: Breusch-Godfrey serial correlation LM test	1.283	0.126
Autoregressive conditional Heteroskedasticity: ARCH LM test.	0.924	0.274

Source: Authors' Calculations.

The results reported in the table above suggest that the model was well specified on the basis of the Ramsey RESET test and serially uncorrelated based on the Breusch-Godfrey serial correlation LM test. The ARCH autoregressive conditional heteroskedasticity test shows that there is no presence of volatility clustering in EPC data in Port Harcourt. The Jarque-Bera (JB) test for the residual from ARIMA (2,1,3) as presented in Figure 4, indicates that the residual from ARIMA (2,1,3) model is normally distributed at 5%.

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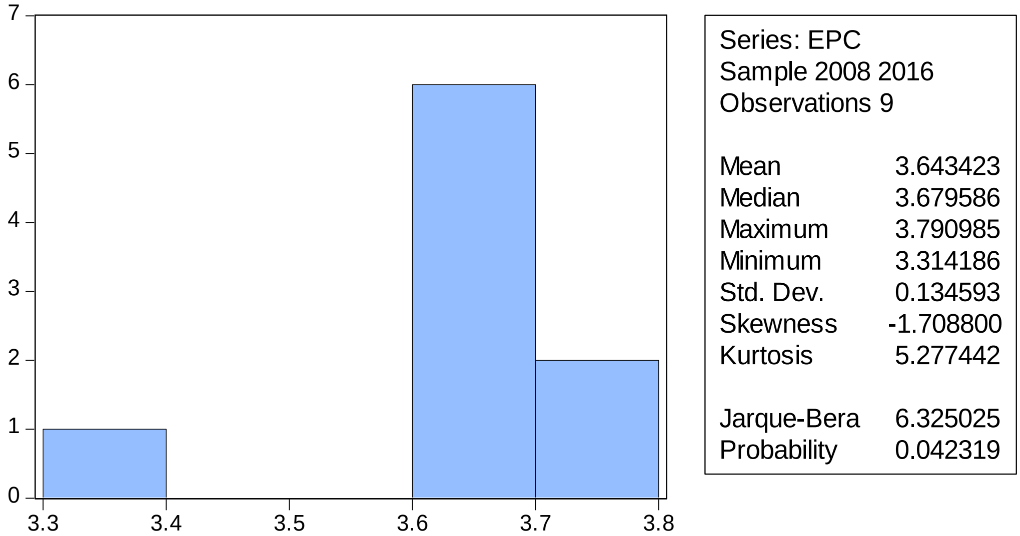

Figure 4 Histogram and normality test for ARIMA (2, 1, 3) residuals
Source: Authors' Calculations.

In Figure 4, the histogram and normality test are plotted. The mean value of the residuals is 3.6434 and the standard deviation is 0.1345. The values of skewness and kurtosis are -1.71 and 5.27 respectively. This means that the residuals have slight kurtosis and are slightly skewed to the left. Jarque-Bera test shows that the residuals series then reject the null hypothesis of normal distribution at 5% significance level.

4.3.4 Forecast and Forecast Evaluation for ARIMA (2, 1, 3) Model

In the next step, the forecast of EPC series in Port Harcourt using ARIMA (2, 1, 3) model was conducted. E Views software provides the one-step ahead static forecasts which are more accurate than the dynamic forecasts. The duration of forecasts is from 2008Q1 to 2016Q4. The forecasts are plotted in Figure 5.

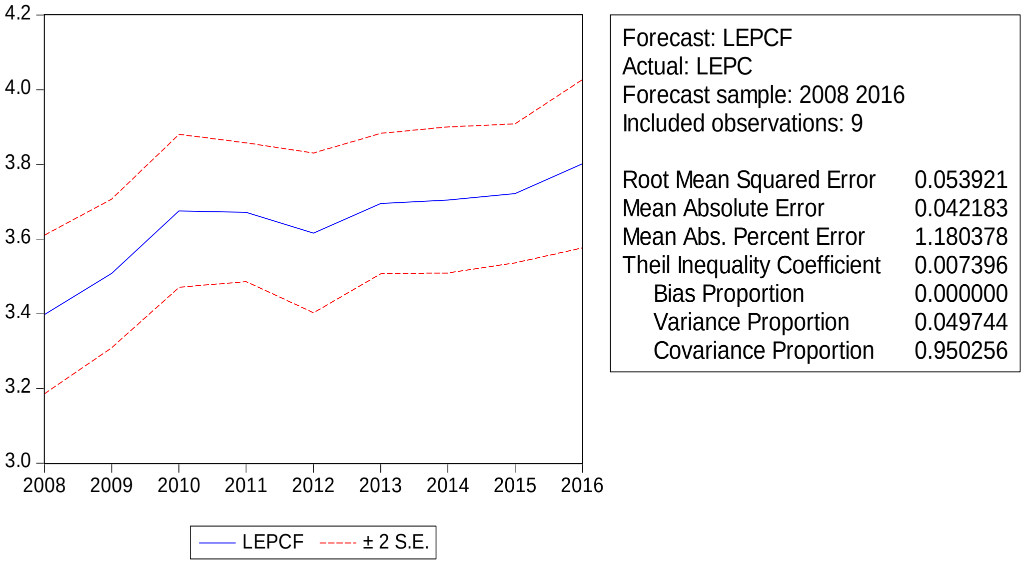

Figure 5 Forecast of EPC by ARIMA (2, 1, 3) model.
Source: Authors' Calculations.

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In Figure 5, the middle line represents the forecast value of EPC. Meanwhile, the lines which are above or below the forecasted EPC series show the forecast with ±2 of standard errors. Some forecasting measurements such as root mean squared error (RMSE), mean absolute error (MAE), and Theil inequality coefficient are shown. These values will be compared with ARDL model forecast performance as stated in our objective. In the forecasting stage, we calculated RMSE, MAE, and Theil Inequality coefficient values from ARIMA (2, 1, 3) model. These are tabulated in Table 6**.** If the actual values and forecast values are closer to each other, a small forecast error will be obtained. Thus, smaller RMSE, MAE, and Theil Inequality coefficient are preferred.
Table 6 below provides information on these forecast measures.
The results show the model is relevant for Electricity Price Forecasting in Port Harcourt.

Table 6: Forecasting Performance of ARIMA (2, 1, 3)

Forecast Performance	**ARIMA(2, 1, 3)**
RMSE	0.0539
MAE	0.0421
Theil Inequality Coeff	0.0073

Source: Authors' Calculations**.**

From Table 6 above, it can be concluded that the model is relevant for Electricity Price Forecasting in Port Harcourt. This is because the values are less than 5 percent at significant level.

Forecast for the residual term of EPF, after sample adjustment for out-of sample forecast from 2017-2025 are reported.

Years	Actual Electricity Price	Forecast Values of electricity Price
2008	27.5	-
2009	37.24	-
2010	38	-
2011	38.11	-
2012	39.63	-
2013	39.72	-
2014	40.05	-
2015	42.04	-
2016	44.3	-
2017		44.585
2018		45.113
2019		45.3574
2020		45.6
2021		45.81
2022		46.0195
2023		46.7185
2024		47.3826
2025		47.78

Source: - Author's calculation.

4.3.5 Model II: Regression Model

In this section, the hypotheses attested using multiple regression analysis. Firstly, the assumptions of ordinary least square (OLS) method are tested. Next the parameters of the regression model are estimated. The table below shows the multiple regressions between electricity prices and the explanatory variables, such as Inflation Rate(INF), Interest Rate (INT), Exchange Rate (EXCH) and Fuel Cost (FC).

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The summary of the regression result in the appendix is shown below:

Variable	Coefficient	t-Statistic	Prob	R^2 = 0.819436
C	2.1258	3.2325	0.0319	Adj. R^2 = 0.63
INF	-0.1896	-0.7379	0.5015	D.W Stat= 2.8867
INT	0.2170	2.2334	0.0893	F- Stat = 4.5382
EXCH	0.3555	0.8422	0.4471	Prob (F-Stat) =0.0860
FC	-0.0644	-0.1779	0.8675	

Source: Author's Computation.

OLS

Dependent Variable: EPC
Method: Least Squares
Date: 04/26/07 Time: 12:13
Sample: 2008 2016
Included observations: 9

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.125788	0.657638	3.232461	0.0319
INF	-0.189545	0.256868	-0.737907	0.5015
INT	0.216949	0.097136	2.233447	0.0893
EXCH	0.355542	0.422139	0.842239	0.4471
FC	-0.064423	0.362234	-0.177850	0.8675

R-squared	0.819436	Mean dependent var	3.643423
Adjusted R-squared	0.638872	S.D. dependent var	0.134593
S.E. of regression	0.080882	Akaike info criterion	-1.891472
Sum squared resid	0.026168	Schwarz criterion	-1.781902
Log likelihood	13.51162	Hannan-Quinn criter.	-2.127922
F-statistic	4.538204	Durbin-Watson stat	2.886652
Prob(F-statistic)	0.086036		

ECM

Last updated: 04/26/07 - 12:14
Modified: 2008 2016 // makeresid

2008	-0.083593
2009	0.109562
2010	-0.037829
2011	-0.030868
2012	0.063526
2013	-0.012985
2014	-0.014060
2015	0.016736
2016	-0.010490

DESCRIPTIVE STATISTICS

	EPC	INF	INT	EXCH	FC
Mean	3.643423	2.438228	2.018582	5.154388	4.512987
Median	3.679586	2.564949	2.127041	5.068904	4.540098
Maximum	3.790985	2.753661	2.403335	5.717028	4.973971
Minimum	3.314186	2.091864	1.252763	4.927254	4.120662
Std. Dev.	0.134593	0.233098	0.366746	0.236521	0.308290
Skewness	-1.708800	-0.442593	-1.094385	1.623793	0.011196

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Kurtosis	5.277442	1.744151	3.134052	4.675619	1.691577
Jarque-Bera	6.325025	0.885266	1.803255	5.007945	0.642177
Probability	0.042319	0.642343	0.405908	0.081760	0.725359
Sum	32.79081	21.94405	18.16724	46.38949	40.61688
Sum Sq. Dev.	0.144921	0.434677	1.076019	0.447537	0.760344
Observations	9	9	9	9	9

$EPC = \alpha_0 + \alpha_1 INF + \alpha 2INT + \alpha_3 EXCH + \alpha_4 FC + \varepsilon_t$ (1)
EPC = 2.1258 – 0.1896INF + 0.2170INT +0.3555EXCH - 0.0644FC (2)
T Stats = (3.2325) (-0.7379) (2.2334) (0.8422) (-0.1779) (3)
P-value = (0.0319) (0.5015) (0.0893) (0.4471) (0.8675) (4)

The regression result above conforms to the a-priori expectations as earlier specified in the model. Interest rate is significant at 5% level of significance, while others are insignificant. The coefficients of the explanatory variables INT and EXCH are both positive, indicating a direct relationship between Electricity Price for commercial class and these two variables. Also, the parameter coefficient of INF and FC are negative indicating an indirect relationship electricity price for commercial and inflation rate and fuel cost. The R^2 also known as the coefficient of determination or coefficient of multiple determination indicate goodness of fit of the model and it is also statistically significant. It indicates that the model explains the variability of the response data around its mean to a reasonable extent. The adjusted R^2 is statistically significant which indicates that after taking into accounts the number of regressors, the model explains about 82% of the variations in electricity price for commercial class. The F – statistics which measures the overall goodness of fit of the model and its probability of 0.0860 is statistically insignificant. The parameter coefficients of the explanatory variables are statistically insignificant at a p-value of 5%.

4.4 Discussion of Findings

This research work has empirically verified and discussed some of the economic and technical factors expected to have significantly influence electricity price namely: inflation rate, interest rate, exchange rate and fuel cost. Findings revealed that only interest rate is significant at 10% level of significance. While inflation rate, exchange rate and cost of fuel are insignificant at 5% level of significance.

This might be explained by the fact that in Nigeria, electricity prices are generally lower than the production cost. Also, to a reasonable extent it was considered as a public welfare service to be provided by the government. This finding therefore agreed with the views of Okoro and Chikuni (2007). Despite the Multi Year Tariff Order and economic factors suggested being involved in its derivation. Empirically, inflation rate, exchange rate and cost of fuel cannot be said to influence the price at 5% level of significance.

Besides, as there was no transparent commercial electricity tariff setting framework that reflected the true price of electricity in Nigeria prior to 2008. Owing to this fact, the tariff setting cannot be set in a way whereby consumer begins to pay the true cost of electricity immediately. Federal Government of Nigeria (FGN) is providing a subsidy to help introduce a viable tariff for the power industry. The tariff takes the form of a per unit payment which reduces each year in order to allow the gradual introduction of a viable industry tariff Odubiyi and Davidson (2010).
Furthermore, there is no stable power supply in Nigeria yet.

ARIMA Model

The study used the correlogram for autocorrelation function (ACF) and partial autocorrelation function (PACF) of the second order difference of EPC series to identify and estimate a parsimonious ARIMA model. Diagnostic tests for serial correlation (Breusch-Godfrey serial correlation test), heteroskedasticity (ARCH test), normality (Jarque-Bera test), and specification error (Ramsey RESET test) of the model were performed. The results suggested that the model was well specified on the basis of the Ramsey RESET test and serially uncorrelated based on the Breusch-Godfrey serial correlation LM test. The ARCH autoregressive conditional heteroskedasticity test showed that there was no presence of volatility clustering in electricity price for commercial class of Port Harcourt Distribution Company.

The Jarque-Bera (JB) test for the residual from ARIMA (2, 1, 3), indicated that the residual from ARIMA (2, 1, 3) model was normally distributed at 1%.

Thereafter, in-sample forecast of EPC dynamics using the ARIMA (2, 1, 3) model was conducted and the forecast performance evaluated using Root Mean Square Error (RMSE), MAE, and Theil Inequality coefficient. The ARIMA (2, 1 ,3) univariate model was able to produce forecasts based on the historical patterns in the data. The results suggested that the model was relevant for forecasting electricity price.

This follows closely the approach adopted by Andersson and Bergman 1995 by using a numerical model in order to analyse electricity output and prices.

Objective One

Ascertain whether inflation rates of the country significantly influence electricity price of commercial class of Port Harcourt Distribution Company.

This study reveals that decrease in the Consumer Price Index which measure inflation will increase the price of electricity of the commercial class of Port Harcourt Distribution Company. Hence, an indirect relationship exists between inflation rates and electricity price.

Objective Two

Determine whether interest rates significantly influence electricity price of commercial class of Port Harcourt Distribution Company.

The study reveals a positive or direct relationship between interest rates and electricity price of commercial class of Port Harcourt Distribution Company. Hence, the higher the interest rate, the higher the price of electricity.

Objective Three

Examine if exchange rates significantly impact on electricity price of commercial class of Port Harcourt Distribution Company.

The country's foreign exchange does not have a significant influence on electricity price, this negates the view of (Ferkingstad, 2010) that a direct relationships was detected between Spanish electricity prices and USD/Euro exchange rate in the sense that Spanish electricity prices are affected by USD/Euro exchange rate in the short run.

Objective Four

Investigate whether cost of fuel affect electricity price of commercial class of Port Harcourt Distribution Company.

Surprisingly, the parameter coefficient of fuel cost is negative which reveals that an indirect relationship exists between cost of fuel and electricity price of commercial class of Port-Harcourt Distribution Company. Hence, the higher the cost of fuel, the lower electricity prices.

4.5 Hypotheses Testing

Four hypotheses were formulated from the research questions of the study. Theses hypotheses are tested below:

H_{01}: The inflation rate of the country do not significantly influence electricity price of commercial class of Port Harcourt Distribution Company.

The regression model in equation (2) has shown that inflation rate does not have significant relationship at 5% on electricity price of commercial class of Port Harcourt distribution company, hence we do not reject the null hypothesis i.e the inflation rate of the country do not significantly influence electricity price.

H_{02}: Interest rates in the country do significantly influence electricity price of commercial class of Port Harcourt Distribution Company.

In equation (3), our test has revealed that Interest rate have a significant relationship at 5% on electricity price for the commercial class of Port Harcourt Distribution Company. Therefore, we reject the null hypothesis that interest rates in the country do not significantly influence electricity price of Port Harcourt Distribution Company.

H_{03}: Exchange rates do not significantly impact on electricity price of commercial class of Port Harcourt Distribution Company.

The result of our test revealed that exchange rate does not have a significant effect on electricity price of the commercial class of Port Harcourt Distribution Company. Therefore we do not reject the null hypothesis at 5% significant level that exchange rates do not significantly impact on electricity price of commercial class of Port Harcourt Distribution Company. This is synonymous with the work of Knittel and Roberts 2005; Janczura and Weron (2010), implying that exchange rate and fuel price increases have a clear negative impact on electricity price volatility while exchange rate and oil price decreases do not significantly affect the electricity price.

H_{04}: Cost of fuel do not significantly affect electricity price of commercial class of Port Harcourt Distribution Company.

The result from our test revealed that fuel cost does not have significant influence on the electricity price of commercial class of Port Harcourt Distribution Company. Therefore, we do not reject the null hypothesis at 5% level of significance that fuel cost do not significantly

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affect electricity price of commercial class of Port Harcourt Distribution Company.

V. CHAPTER FIVE
SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The objectives of this study were to identify a univariate autoregressive integrated moving average (ARIMA) model and regression model to estimate and analyze the forecasting performance of the estimated model.

5.2 Summary of Findings

The findings of the study are as follows:

A. Exchange rate does not have a significant positive influence on electricity prices.
B. Cost of fuel does not have a significant influence on electricity price.
C. During the period under review, interest rate has a significant positive influence on electricity price.
D. Inflation does not have a significant influence on electricity price.

5.3 Conclusion

The power sector plays a key role considering the multiple effects a stable electricity supply on the productive sector of the economy. Before any customers in the electricity industry can pay for the real cost of electricity, the supply must at least be steady. Which may enable the customer choose willingly between or among other source of generating electricity.

Also, foreign investment in the electricity sector may be impossible if real cost of electricity is not charged.

5.4 Recommendation

a. Even though the introduction of competition has succeeded reasonably well, but there is no real competition in the retail business in Nigeria, before the small consumers could easily change from one electricity supplier to another, hence, competition should be introduced.
b. In order to keep the sector financially viable, the government is expected to close the gap between the required tariff and what consumers are actually billed. Unlike the previous uniform pricing regime, only the most needy tariff classes would enjoy a subsidy. The gradual removal of the subsidy is expected to reduce the burden on consumers while allowing them to adjust to the new price. The exit of the Federal government subsidy would occur when power availability rises sufficiently to enable a further rebalancing of the tariff.
c. The investment climate must be made attractive to motivate genuine investors. There is need for a conducive economic, social and political environment in the country since the sector cannot operate in vacuum of its environment. Inputs of electricity production are tradable goods (gas and fuel), which are normally denominated in foreign currency, but the outputs are mostly sold within the country in local currency. The achievement of efficient supply of electricity at affordable tariffs therefore, hinges on a stable exchange rate.

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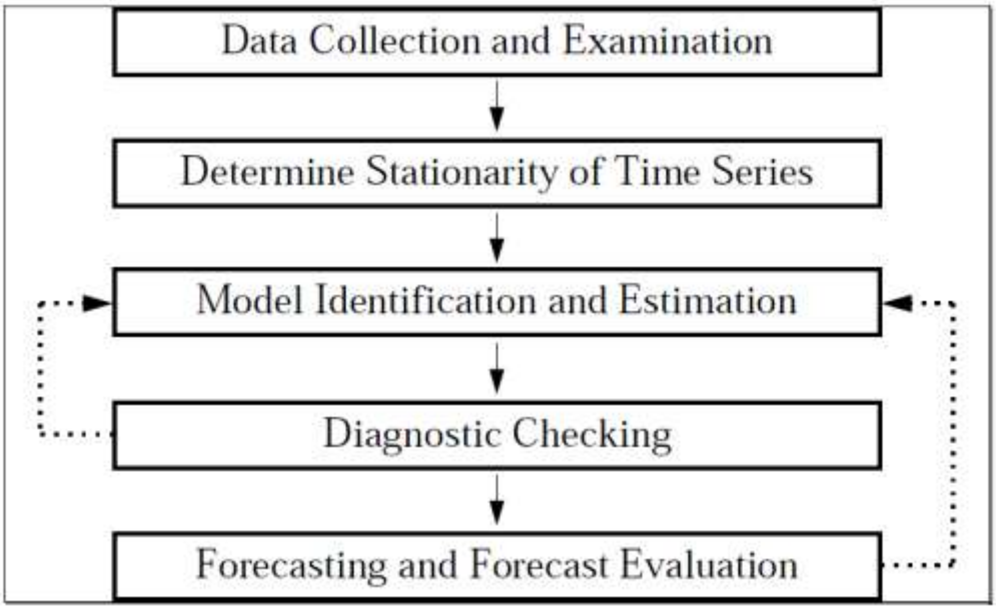
APPENDIX 1



ARIMA FORECASTING PROCEDURE

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APPENDIX 2

Tariff classes

Customer Classification	Description	Remarks
Residential		A consumer who uses his premises exclusively as a residence- house, flat or multi- storied house
R1	Life-Line (50 kWh)	
R2	Single and 3-phase	
R3	LV Maximum Demand	
R4	HV Maximum Demand (11/33 KV)	
Commercial		A consumer who uses his premises for any purpose other than exclusively as a residence or as a factory for manufacturing goods.
C1	Single and 3-phase	
C2	LV Maximum Demand	
C3	HV Maximum Demand(11/33 KV)	
Industrial		A consumer who uses his premises for manufacturing goods including welding and ironmongery
D1	Single and 3-phase	
D2	LV Maximum Demand	
D3	HV maximum Demand (11/33 KV)	
Special		Customers such as agriculture and agro-allied industries , water boards, religious houses, government and teaching hospitals, government research institutes and educational establishments.
A1	Single and 3 Phase	
A2	LV Maximum Demand	
A3	HV Maximum Demand (11/33 KV)	
Street Lighting		
S1	Single and 3-phase	

APPENDIX 3

YEAR	EPC (N/KWh)	INF (% per year)	INT (% per year)	EXCH (N /US dollar)	FC US-$/mmbtu
2008	27.5	13	3.5	138	61.6
2009	37.24	13	5.07	150	61.6
2010	38	13	11.06	153.13	70.8
2011	38.11	13	10.32	162	81.5
2012	39.63	12.2	8.39	156	93.7
2013	39.72	8.5	8.78	159	103.4
2014	40.05	8.1	7.21	182.85	114.8
2015	42.04	9	7.7	198	123.87
2016	44.3	15.7	9.37	304	144.6

Source: NNPC statistical bulletin, 2016. National Bureau of Statistics (NBS).

RESULTS

OLS

Dependent Variable: EPC
Method: Least Squares
Date: 04/26/07 Time: 12:13
Sample: 2008 2016
Included observations: 9

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.125788	0.657638	3.232461	0.0319
INF	-0.189545	0.256868	-0.737907	0.5015

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INT	0.216949	0.097136	2.233447	0.0893
EXCH	0.355542	0.422139	0.842239	0.4471
FC	-0.064423	0.362234	-0.177850	0.8675

R-squared	0.819436	Mean dependent var	3.643423
Adjusted R-squared	0.638872	S.D. dependent var	0.134593
S.E. of regression	0.080882	Akaike info criterion	-1.891472
Sum squared resid	0.026168	Schwarz criterion	-1.781902
Log likelihood	13.51162	Hannan-Quinn criter.	-2.127922
F-statistic	4.538204	Durbin-Watson stat	2.886652
Prob(F-statistic)	0.086036		

ECM

Last updated: 04/26/07 - 12:14
Modified: 2008 2016 // makeresid

2008	-0.083593
2009	0.109562
2010	-0.037829
2011	-0.030868
2012	0.063526
2013	-0.012985
2014	-0.014060
2015	0.016736
2016	-0.010490

DESCRIPTIVE STATISTICS

	EPC	INF	INT	EXCH	FC
Mean	3.643423	2.438228	2.018582	5.154388	4.512987
Median	3.679586	2.564949	2.127041	5.068904	4.540098
Maximum	3.790985	2.753661	2.403335	5.717028	4.973971
Minimum	3.314186	2.091864	1.252763	4.927254	4.120662
Std. Dev.	0.134593	0.233098	0.366746	0.236521	0.308290
Skewness	-1.708800	-0.442593	-1.094385	1.623793	0.011196
Kurtosis	5.277442	1.744151	3.134052	4.675619	1.691577
Jarque-Bera	6.325025	0.885266	1.803255	5.007945	0.642177
Probability	0.042319	0.642343	0.405908	0.081760	0.725359
Sum	32.79081	21.94405	18.16724	46.38949	40.61688
Sum Sq. Dev.	0.144921	0.434677	1.076019	0.447537	0.760344
Observations	9	9	9	9	9

Dependent Variable: EPC
Method: Least Squares
Date: 04/26/07 Time: 12:13
Sample: 2008 2016
Included observations: 9

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.125788	0.657638	3.232461	0.0319
INF	-0.189545	0.256868	-0.737907	0.5015

INT	0.216949	0.097136	2.233447	0.0893
EXCH	0.355542	0.422139	0.842239	0.4471
FC	-0.064423	0.362234	-0.177850	0.8675

R-squared	0.819436	Mean dependent var	3.643423
Adjusted R-squared	0.638872	S.D. dependent var	0.134593
S.E. of regression	0.080882	Akaike info criterion	-1.891472
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Variable	Coefficient	Std. Error	t-Statistic	Prob.
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Prob(F-statistic)	0.086036		

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |* . |	. |* . |	1	0.209	0.209	0.5415	0.462
. |* . |	. | . |	2	0.096	0.055	0.6718	0.715
. | . |	. | . |	3	0.061	0.032	0.7324	0.866
. | . |	. *| . |	4	-0.056	-0.083	0.7946	0.939
. *| . |	. *| . |	5	-0.103	-0.086	1.0548	0.958
. *| . |	. *| . |	6	-0.129	-0.091	1.6053	0.952
. **| . |	. *| . |	7	-0.243	-0.195	4.5232	0.718
. **| . |	. **| . |	8	-0.335	-0.266	15.649	0.048

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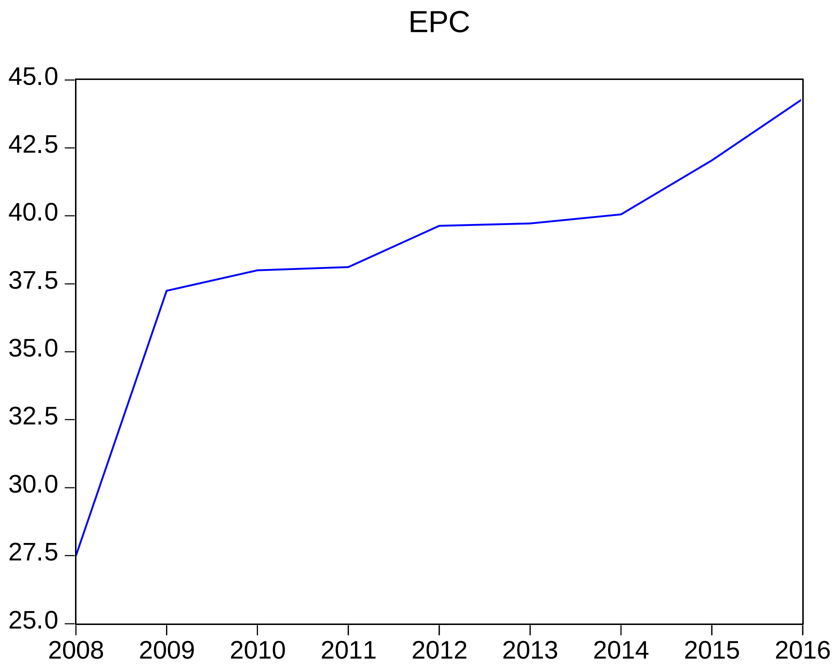
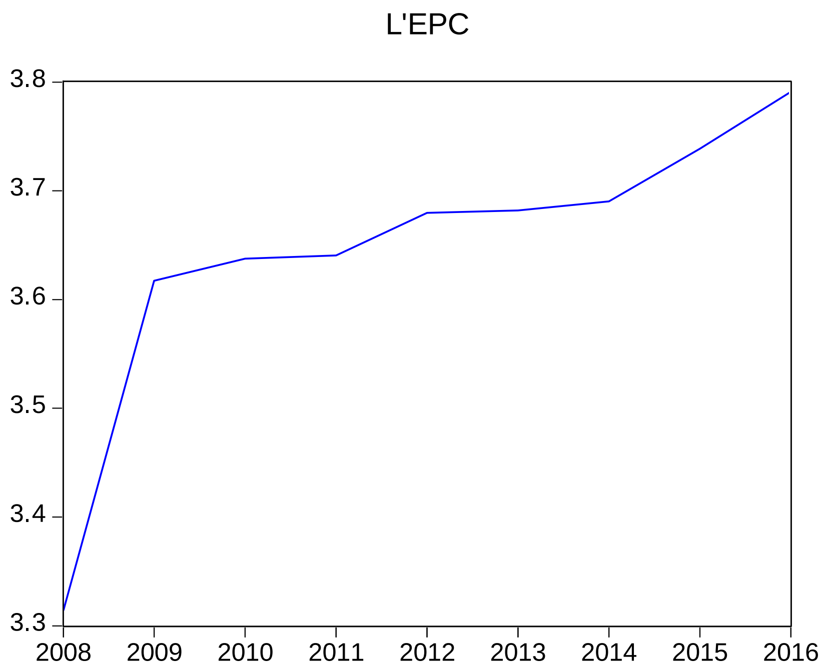
EPC



LEPC



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FORECAST