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Non Linear Time Series Modelling of the Diesel Prices in Kenya

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Abstract
Modelling and forecasting diesel prices are a vital concern in most developing economies. A better understanding of a country's diesel price situation and future prices can facilitate users to make appropriate decisions regarding buying and selling patterns and also to the government in making appropriate policy measures to maintain low and stable prices. The study employed the Autoregressive Integrated Moving Average Model (ARIMA) that could capture the volatility eminent in the fuel prices and forecasting. Findings of the study indicate that the monthly diesel prices in Kenya were non-stationary implying the non stability with regards to the diesel market. The study found that an ARIMA (2,1,2) model was suitable and valid model for estimating volatility and forecasting the diesel prices. The study recommends the government of Kenya through the Energy Regulatory Commission (ERC) should adopt a stable form of diesel prices that are low so as to improve the decisions regarding buying and selling patterns among the users and to improve economic growth rate by ensuring that the cost of production has been put at minimal levels diesel being one of the contributors of production inputs.
Keywords: Diesel Prices, ARIMA, Modeling, Volatility, Forecasting, Kenya

Introduction

In today's world where fuel prices are increasing as a result of a spiralling demand and diminishing supply, the fuel users need to choose a cost effective fuel plan to meet their needs. Diesel fuel is cheaper than other fuels; the diesel engines have also proved to be extremely efficient and cost effective. The diesel engine, for example in the automobiles, provides a higher mileage making it an obvious choice for heavy duty transportation and equipment. In Kenya, diesel fuel is mostly used in the transportation, industrial, construction, fishing and agricultural sectors, due to the fact that it is extremely effective. Since diesel is a necessary input for many sectors in the economy, a proper and timely forecasting of the purchasing and selling of diesel can affect the base for many business entities especially if large amounts of fuel are consumed. Kenya does not have its own fuel reserves and therefore depends on importing mainly from the Middle East countries such as Kuwait, Iran, Saudi Arabia, and Libya among others.

In normal cases, a fuel user who expects to use large amounts of diesel and expects the prices to rise in the future will enter into a forward contract with a fuel distributor to buy the fuel at a pre-agreed future price which is lower than what they anticipate the future price to be. This permits a purchaser to lock in a diesel price and provides protection from future price increases. However, during periods of high price volatility, the timing of when to enter into forward contracts depends on the users' ability to accurately forecast fuel prices in order to make better fuel purchasing decisions.

Prior to 2002, the diesel prices were stable, but this has not been the case in the recent years. Recent developments in the energy sector have made it impossible to forecast diesel prices as both price and variability have dramatically increased. In the 2008 global financial crisis, the international demand of oil went down and the prices of crude oil decreased, however the price of diesel has remained high than the recent past.

The main problem at hand therefore is the non stability of the diesel price because keeps on changing due to several but not limited to changes in demand and supply, seasonality in demand, influence by OPEC and political unrest in the oil producing countries. This makes it difficult for the diesel providers and users to make meaningful decisions regarding the purchasing and selling patterns. Thus, an effective and efficient model to forecast the volatile diesel prices is of utmost importance for the country's economy at large.

The purpose of this paper is two fold; first examine examined the uncertainty in the diesel market with regard to the changing prices of diesel. secondly, to develop a non linear time series model with the help of Autoregressive Integrated Moving Average (ARIMA) model that would help to forecast the diesel prices in order to improve on the certainty of making future decisions relating to prices in the Kenya's energy sector, in particular diesel market.

Literature Review

Energy Sector in Kenya

Petroleum has been the most important source of energy in Kenya. Petroleum fuels are imported in form of crude oil for domestic consumption through the port of Mombasa and also refined in the same region at Changamwe. Fluctuations in international prices have directly affected domestic prices in the country. The international price of Murban crude oil rose by approximately 46% from US$ 62.05 per barrel in December 2006 to US$ 90.60 per barrel in December 2007 and about US$ 140 per barrel in August 2008,before decreasing to less than US$ 50 by March 2009.The total quantities of petroleum imports registered a growth of 16.4 % to stand at 3691.8 thousand tonnes in 2007.The total import bill of petroleum products also rose by 7.1% in 2007 compared to 8.9% in 2006 (Kutot, Menjo and Jepkwony, 2012).

The energy market is that market that deals specifically with the trade and supply of energy. This market may refer to the electricity market, kerosene market, petrol market, diesel market and gas market. In Kenya, the energy market is as a result of the government creating an energy policy that encourages the development of an energy industry in a competitive manner. Energy markets have been liberalized in some countries; they are regulated by national and international authorities so as to protect consumer rights and avoid monopolies. In Kenya, the market is regulated by the Energy Regulatory Commission (ERC).

The Kenyan Energy regulatory commission (ERC) was established under the Energy Act, 2006. Following the operationalisation of the Energy Act, 2006, the Energy Regulatory Board (ERB) became Energy Regulatory Commission (ERC). The objects and functions of ERC as given in the act include regulating the importation, exportation, transportation, refining, storage and sale of petroleum and petroleum products. Therefore, ERC provides licenses of petroleum imports, export, transport, storage, refining and sale. Construction permits are also issued by ERC for all petroleum related facilities in order to check proliferation of substandard sites. As part of its mandate the ERC fixes the fuel prices at the 15th of every month.

Price Control in the Energy sector

The energy sector in the worldwide is characterized by monopolistic structures that are a hindrance to the economic efficiency that is associated with competitive markets. Monopolies are sole suppliers of commodities in a market that has a characteristic of no competitors (Jack and Ernie, 2007).The monopolies obtain these powers from factors which include; ownership of scarce resource, prohibitive cost of putting infrastructure and economies of scale. The role regulation is therefore to deal with this market failure and promote efficiency, competition, investment and private sector participation and to promote consumer interests in terms of affordable, quality of service and sustainability.ERC has introduced oil price controls to help regulate the energy sector.

A price control is a restriction on the price that should be charged on goods and services in a market. The aim of price control is to make the essential commodities easily available to the public. Such commodities include maize, maize flour, wheat, wheat flour, rice, cooking fat, sugar, paraffin, diesel and petrol (Ephraim, 2009).The big question however is, do the price controls on these commodities achieve what they are intended to? Price controls have an effect of distorting the allocation of natural resources; this is because they reduce the entry and investment of resources in the long run. If a price control is fixed on diesel prices such that the diesel appears cheaper, there will be increased demand for the fuel. However, the fuel firms will not be willing to supply more at the low prices as they pose a threat to their profits. The overall effect is that there will be a shortage of diesel in the country. Lipsey and Chirystal (2007) argue that the best situation is when the market is free and runs on its own such that the best price for commodities will be when demand and supply are in equilibrium.

Effects of Diesel Prices to the Economy

Diesel is a vital fuel to the economy in that most of the sectors depend on it for running the machines. It is used in the transport sector, agricultural sector, industrial sector and many others to run machines and locomotives. It is mostly preferred than other fuels for its efficiency. For these major applications, it is a key player in the development on the country. Diesel being a fuel is an input to the production of goods and services. When the diesel prices are low,the marginal cost of production will be low and thus the profits will be high (Dinesh and Sivamohan, 2001).This will attract more investors in the country and thus more businesses will be set. The GDP will in turn go upfor investments will stimulate it .A high GDP translates to an improvement in economic growth in a country.On the other hand,high diesel prices are a hindrance to economic growth. High diesel prices increase the marginal cost of production.The high cost of production is passed on to the price of goods and services and thus an increase in the price of diesel will lead to a high price of goods and services.The consumers will then demand less of the commodities thereby chasing investors out of the economy as their profits will be threatened to go down.A decrease in the level of investments is an inhibiting factor to economic growth as the GDP in the country will be low (Kumar, 2008).

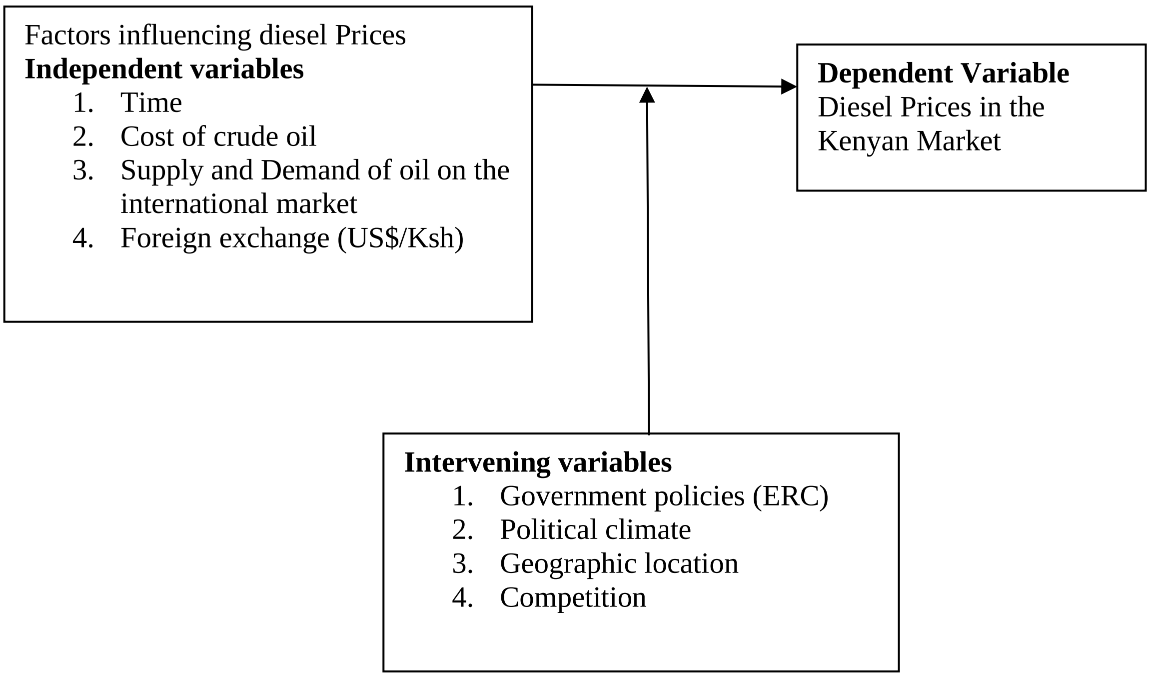
Diesel Prices and Inflation

Inflation is the persistent increase in the prices of commodities with time. Inflation in Kenya is caused by several factors which include a rise in the cost of production; weakening of the Kenyan shilling with respect to the dollar, increase in money supply, increase in government expenditure among others.Diesel is an important input in the production of goods and services. It is one of the costs of productionthat manufacturers incur in their production process. Being a cost, it plays a major role in the determination of prices for the commodities. This makes it have an effect to the inflation rates in the country.

Syed,Muhammad, Amir and Ammar (2012) argued that diesel being one of the raw materials in production and provided that if raw materials increase in price, this leads to the cost of production increasing. This in turn leads to the producers increasing prices to maintain their profits. This kind of inflation is called cost-push inflation. Moses (2009) argues that oil prices diesel being one of them seem to be highly correlated with inflation which s quite visible in the period following liberalization.If a country has to maintain a smooth economic growth rate; such factors such as inflation have to be maintained to the lowest levels as possible. The government of Kenya has tried to maintain the prices through ERC though it has at times been difficult to keep them low due to the energy crisis in the global market.

Conceptual Framework

A concept is an idea or abstract inferred or derived from specific instances (Kombo and Tromp, 2006). It is a word or phrase that symbolizes several interrelated ideas. A conceptual framework is thus a set of broad ideas and principles taken from relevant field of inquiry and used to structure a subsequent presentation. There are a set of three key variables in this research. They include the independent variable, the dependent variable and the intervening variables.



The figure above represents the various variables affecting the diesel prices in

Kenya. First, the independent variables represent a set of factors that influence the price of diesel; time,cost of crude oil and the energy demand. The price of diesel is highly influenced by time; it keeps on changing with time and thus displaying volatility trends. Prices of crude oil also influence the price of diesel in the local market. If the price of crude oil goes up, then the diesel prices also go up and vice versa. International demand and supply of energy, foreign exchange of US$ with respect to Kenyan Shilling also influences prices of diesel on the Kenyan market.

A high international demand of energy outweighs the available supply thereby the market finding equilibrium by pushing the prices of diesel up. On the other hand a low demand will mean that the supply is in excess of it and thus the price will be low. Other than the independent variables, we also have other variables that influence the price of diesel which is the dependent variable.Theseare the intervening variables and include government policies, the political climate, geographical location and competition. Government policies and in specific taxation influence the price of diesel, taxation is a source of government revenue; in Kenya it contributes the biggest share of revenue raised. Taxation of diesel increases the pump price and this may vary depending on the various rates that the government may pose on it. Political climate is another influencing factor; when there are political unrests in the oil producing countries, a shortage occurs as it is not possible to import from those countries. The effect of the shortage is that importing countries will have to pay a high price in order to get the limited supply and thus the prices of the products such as diesel goes up. Geographical location also influences the prices; the far away Kenya is from the oil producing countries that it imports from, the higher the cost of transportation and this is then translated to the diesel prices. Competition by the diesel sellers is another intervening variable .Competing trader will sell their fuel at a low price in order to attract customers from rivals. The effects of the completion will be low pump prices; therefore pump prices will depend with the level of completion in the market.

Econometric Methodology

Research Design

The research design adopted was a time series design. This is because the diesel prices have a tendency of changing with time. Monthly diesel prices from October 2005 to August 2012 were used as sufficient time series data and were fitted in the ARIMA model to obtain estimates that can help to forecast the diesel prices in the future period using past data.

ARIMA Model

ARIMA model is one of the time series models used in forecasting. This model unlike others does not assume knowledge of any underlying economic model or structural relationships. It is assumed that values of the past series and the previous disturbance terms have information for the purposes of forecasting. The major advantage of ARIMA is that it requires data on the time series in question only.

Prerna (2012) provides that the ARIMA model is a modification of the ARMA model. ARMA models represent a combination of the Auto Regressive (AR) and Moving Average models.The application of the ARIMA model to time series analysis is due to Box and Jenkins (18).The ARIMA model was applied in this study to forecast the diesel prices using monthly prices data from the Energy Regulatory commission (ERC).

Model Specification

This section provides a general outlook of the Moving Average (MA) model, the Autoregressive (AR) Process, the Autoregressive Moving Average Process (ARMA) and the Autoregressive Integrated Moving Average (ARIMA) process.

Moving Average model (MA)

Moving Average models were as a result of an invention by Slutsky in 1937 (Makridaskis and Hibon, 1995).An MA process is one in which the current value of a time series depends upon current and past random error variables.A first order MA process can be expressed as

$$Y_t = \theta_1 \varepsilon_{t-1} + \varepsilon_t \quad (1)$$

In general,a qth- order moving average model (MA) is non-stationary and has the general form given as;

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

$$\sum_{i=0}^{q} \theta_i \varepsilon_{t-i}, \qquad \varepsilon_{t\sim} WN(0\sigma^2) \quad (3)$$

where

Y_t = Response (dependant) variable at time t

μ =Constant term of the process

$\theta_1, \theta_2, \dots \theta_q$= Coefficients to be estimated

ε_t = Error term at time, where $\varepsilon_t \sim WN(O, \sigma^2)$

$\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}$=Error terms in the previous periods that are incorporated in the response variable.

An Autoregressive (AR) Process

Autoregressive (AR) models were first introduced by Yule in 1926 (Makridakis and Hibbon 1995). An AR process is one in which the current value of a time series depends upon the past values of a time series and the random error. A first order AR process can be expressed as:

$$Y_t = \emptyset_1 Y_{t-1} + \varepsilon_t, \qquad \varepsilon_{t\sim} WN(0\sigma^2) \quad (4)$$

In general, a pth-order autoregressive model AR (p)is non-stationary and has the general form given by;

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots \emptyset_p Y_{t-p} + \varepsilon_t \quad (5)$$

$$= \sum_i^p \emptyset_i Y_{t-i} + \varepsilon_t, \qquad \varepsilon_{t\sim} WN(0\sigma^2) \quad (6)$$

where

$Y_{t=}$Response (dependent) variable at time t

$Y_{t-1,} Y_{t-2}, \dots, Y_{t-p}$ = Response variable at time lags t -1, t -2…t– p, respectively

$\emptyset_{0,} \emptyset_1 \emptyset_2 \dots, \emptyset_p$ = Coefficients to be estimated

$\varepsilon_{t=}$ Error term at time t. where $\varepsilon_t \sim WN(O, \sigma^2)$

Auto Regressive Moving Average model: ARMA (p,q)

The ARMA model is as a result of combination of the AR and MA models by Wold in 1938 (Makridakis and Hibbon 1995).He showed that ARMA processes can be used to model all time series as long as the appropriate order of p, the number of AR terms and q, the number of MA terms was appropriately specified. An ARMA (p,q) has the general form given as;

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots \emptyset_p Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \quad (7)$$

Auto Regressive Integrated Moving Average model: ARIMA (p,d,q)

The ARIMA model is a modification of the ARMA models arrived at by transforming the time series data to Stationarity. ARIMA models became highly popular in the 1979s among academics, in particular when it was shown through empirical studies (Cooper,1972) that they could outperform the large and complex econometric models, popular at that time, in a variety of situations. If we difference the time series *d*,then the model becomes stationary (Ransang and Titida 2006). By applying ARMA (p,q) to it, we say the original time series Auto Regressive Integrated Moving Average model (p, d, q) where *p* is the number of autoregressive terms, *d* is the number of non-seasonal differences and *q* is the number of lagged forecast errors in the prediction equation. Stationarity in the model can be detected by considering the use of the Auto Correlation Function graph (ACF).If a graph of the time series values either cuts off or dies down fairly quickly, then the times series should be considered stationary. If however the graph of the ACF dies down extremely slowly, then the time series values should be considered non-stationary. If the original time series is stationary, *d* = 0 and the ARIMA model reduces to ARMA model.

The difference linear operator (Δ) is given by

$$\Delta Y_t = Y_t - Y_{t-1} = Y_t - BY_t = (1-B)Y_t \tag{8}$$

The stationary series W_t is obtained as the *d*th difference (Δ^d) ofY_t,

$$W_t = \Delta^d Y_t = (1-B)^d Y_t \tag{9}$$

The ARIMA model thus has the general form given by;

$$\emptyset_p(B)(1-B)^d Y_t = \mu + \theta_q B \varepsilon_t \tag{10}$$

or

$$\emptyset_p(B) W_t = \mu + \theta_q B \varepsilon_t \tag{11}$$

Box Jenkins-Methodology

The study focused on the Box-Jenkins (1976) strategy that involves stages of identification, model estimation diagnostic checks and forecasting the time series. The stages are analysed in the below subsections.

Model Identification

This stage involves determining whether the series is stationary or not and determining the tentative model by observing the behaviour of the autocorrelation (ACF) and partial autocorrelation function (PACF) and the resulting correlograms (Al-Zeaud, 2011). Correlograms are the plots of the ACFs and PACFs against lag length. The correlogram can be given as;

$\rho_k = corr(Y_t, Y_{t-k})$ where ρ_k is the autocorrelation of the k^{th}series

The autocorrelation coefficient (ACF) measures the correlation between a set of observations and a lagged set of observation it a time series. The sample autocorrelation coefficient r_k is given by,

$$r_k = \frac{\sum(Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum(Y_t - \bar{Y}_t)^2} \tag{12}$$

where Y_t= The data from the stationary time series

Y_{t+k}= The data from *k* time period ahead of *t*

$\bar{Y}$= The mean of the stationary time series

The estimated partial autocorrelation function (PACF) is used as a guide together with the estimated autocorrelation function in choosing one or more ARIMA models that fit the data available. The idea of Partial autocorrelation is that we want to measure how $Y_t$and Y_{t+k} are related. The following equation gives a good estimate of the partial autocorrelation;

$$\hat{\varphi}_{11} = r_1 \qquad (13)$$

$$\hat{\varphi}_{kk} = \frac{r_k - \sum_{j=1}^{k-1} \hat{\varphi}_{k-1,j} r_{k-j}}{1 - \sum_{j=1}^{k-1} \hat{\varphi}_{k-1,j} r_j} \qquad k = 2,3, \ldots \qquad (14)$$

$$\hat{\varphi}_{kj} = \hat{\varphi}_{k-1,j} - \hat{\varphi}_{kk} \hat{\varphi}_{k-1,k-j} \qquad k = 3,4, \ldots, j = 1,2, \ldots . k-1 \qquad (15)$$

If a graph of the ACF of the time series values either cuts off fairly quickly or dies down fairly quickly, then the time series should be considered stationary. If the ACF graph dies down extremely slowly, then the time series values should be considered non-stationary. If the series is not stationary, it needs to a logarithmic transformation and then converting it to a stationary process by differencing.

The behaviour of the various models on the ACF and PACF can be shown as follows.

Table 1

How to determine the model using the ACF and PACF patterns

Model	ACF	PACF
AR(p)	Dies down	Cut off after lag *q*
MA(q)	Cut off after lag *p*	
ARMA(p,q)	Dies down	Dies down
		Dies down

Estimation of Parameters

The parameters of the model are to be estimated by the least squares method and the maximum likelihood. This method is based on the computations of the innovations $\varepsilon_t$from the values of the stationary variable. The least- squares method minimize the sum of squares,

$$min \sum_t \varepsilon_t^2 \qquad (16)$$

Solving the estimation problem entails writing the above equation in terms of the observed data and the set of parameters $(\theta, \emptyset, \sigma)$. An ARMA (p,q) process for the stationary transformation Y_t can be expressed as;

$$\varepsilon_t = Y_t - \delta - \sum_{i=1}^{p} \emptyset_i Y_{t-i} - \sum_{i}^{q} \theta_i \varepsilon_{t-i} \qquad (17)$$

Diagnostic Checks

This is a Jenkins method of checking whether or not the residuals$\varepsilon_t$were white noise.This is done by checking the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF)coefficients. The assumption made here is that the error term is independent and identically distributed according to a normal distribution.The various checks include; Akaike Information Criteria (AIC), Mean Squared Error (MSE) and Shwartz Bayesian Criteria (SBC).Akaike Information Criteria (AIC) can be generalised by the formula;

$$AIC = 2k - 2\ln(L) \qquad (18)$$

where *k* is the number of parameters in the model and *L* is the maximised value of the likelihood function for the estimated model. Given a set of models, the best model to choose is one with the minimum AIC value The SBC which is also known as the Bayesian Information Criteria (BIC) formula is given as;

$$-2.\ln p(x/_k) = BIC = -2.\ln L + k\, ln(n) \qquad (19)$$

where *x* is the observed data, *n* is the number of observations, *k* is the number of parameters to be estimated, $p(x/_k)$ is the probability of the observed data given the number of parameters and *L* is the maximised likelihood function for the estimated model. The Mean Squared Error (MSE) of an estimator $\widehat{\emptyset}$ with respect to the estimated parameter $\emptyset$ is defined as;

$$MSE = \frac{\sum_{t=1}^{n}(\varepsilon_t)^2}{n} = \frac{\sum_{1}^{n}(y_{t1} - \widehat{y_t})^2}{n} \qquad (20)$$

where *n* is the size of the time series data

Forecasting using the Model

This stage involves getting the precise estimates of the coefficients of the ARIMA model in the identification stage. These estimates are obtained by fitting the time series data to the ARIMA model. This stage also provides some warning signs on the adequacy of the model whereby if the model does not satisfy the adequacy conditions, it is rejected.

Model Application

Not much has been done in forecasting diesel prices. Bajjalieh (2010) forecasted diesel fuel prices using a Composite forecasting model which is an integrated model consisting of the Future-Base Forecasting models and the Structural-Based Forecasts model in Illinois.
Researchers have also participated in the forecasting of other energy models. These studies include; a study by Javier, Rosario, Francisco and Antonio (2003) who used the ARIMA models to predict next-day electricity prices in Spain, Prerna (2012) forecasted natural gas price in London using a time series and nonparametric approach, Syed, Muhammad, Amir and Ammar (2012) investigated on the impact of oil prices on food inflation in Pakistan, Kotut, Menjo and Jepkwony (2012) looked at the impact of petroleum oil price fluctuation in Kenya and Ron, Kilian and Robert (2012) forecasted the price of oil Michigan. It is thus clear that little has been done in Kenya and thus this project aims at exploring the under researched market in the country.

Data description and sources

Time series data for Monthly diesel prices from October 2005 to August 2012 is used in this paper. This data was obtained from Kenya National Bureau of Statistics (KNBS), the Energy Regulatory commission (ERC) and the Ministry of Energy.Data obtained from these sources is considered authentic and can therefore be relied upon for deriving conclusions based on the past. Such data is also considered credible and free from error or any bias.

Data Analysis

Time Series modelling v4.36 statistical software was used to run and analyse the time series data in order to obtain estimates that can be used to forecast future diesel prices. The raw data obtained from Kenya National Bureau of Statistics and the Energy Regulatory commission is entered into the software and run for the ARIMA process. For the data to be run,it has to undergo log transformation to make it easier to transform the data to Stationarity. The values of the parameter estimates for the model were obtained from the output of the run data.The analysis also involves drawing time plots, the ACF and PACF graphs and descriptive statistics. The diagnostic test values; Akaike Information Criteria (AIC), Shwartz Bayesian Criteria (SBC) and the Mean Squared Error (MSE) is also obtained from the analysis.

Results and Discusion

The section specifically discusses the stationarity of the diesel prices and the behaviour of the Autocorrelation graph. The section also outlines the estimation results, a comparison of various models and a display of the equation showing the model chosen. Diagnostic checks and estimation have also been presented and discussed.

Trend and Stationarity properties of the Diesel prices

The preliminary analysis was done by use of time plots for the various series presented in Figures 2 and 3

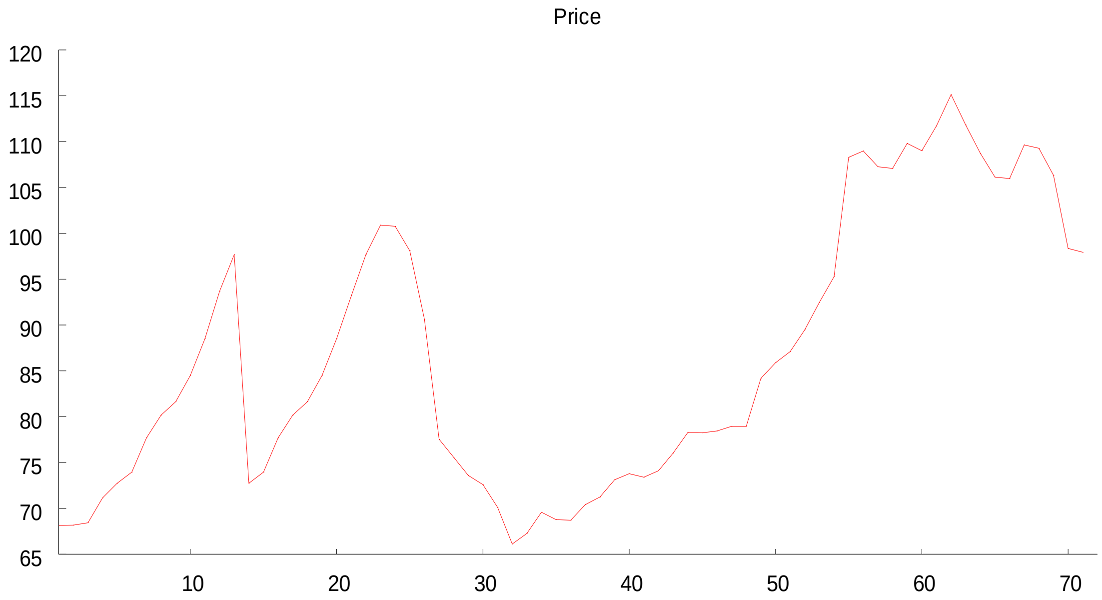


Figure 2: Time plot for the monthly average diesel prices

By inspecting the time plot visually, it clearly shows that the mean and variance are non-constant implying that the data is non-stationary. The non-constant mean and variance provides a suggestion of the utilization of a non-linear model.

The series was transformed to attain Stationarity by taking the first differences of the natural logarithms of the values in each series.The equation representing the transformation is given by $Y_t = \ln(P_t) - \ln(P_{t-1})$ where P_t represents the monthly value for each series. The resulting plots for the returns are presented below:

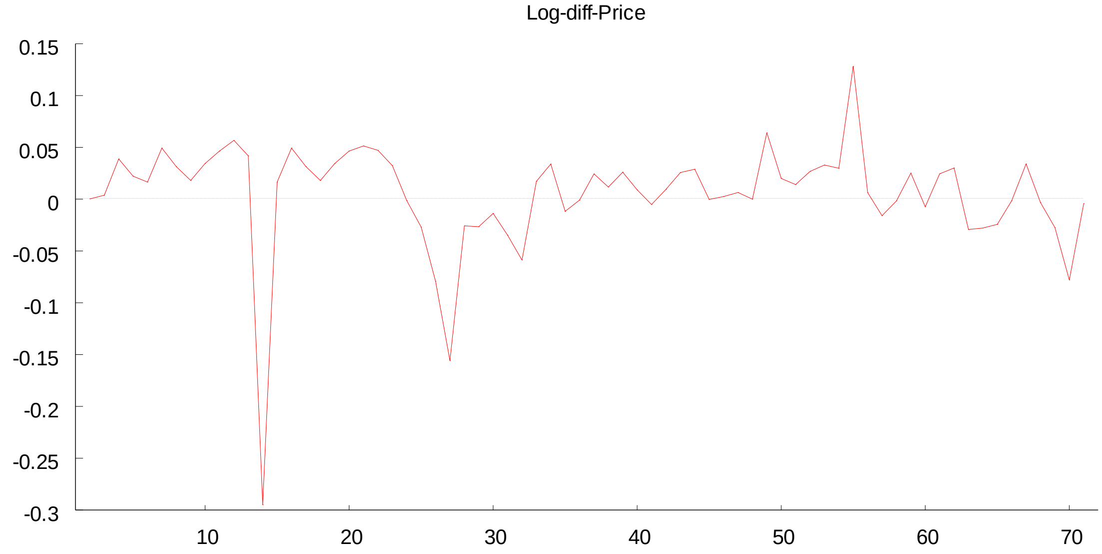


Figure 3: Time plots for log differenced Prices

The time plot of the series now depicts stationarity. The mean and variance show the property of being constant. At lag 13, there is a shock caused by a sharp fall in the diesel prices. This was due to a fall in the price of crude oil in the international market in the month of November 2012.

The analysis involved a total of 93 observations being used. This data displayed a mean of 82.0992 and a standard deviation of 15.9392.The differenced data had a kurtosis of 22.3858 and Jarque Bera test of 1718.66.It was negatively skewed with a Skewness of -3.0677.This means that there were more observations on the left hand side.

Auto-correlation Function (ACF)

Apart from inspection method of checking for stationarity,the autocorrelation function (ACF) of diesel price shown in figure 4 also provides very useful information that is typical of a non-stationary process, where the autocorrelation declines slowly as the number of lags increases. This behaviour is expected of time series likely to have random walk behaviour.

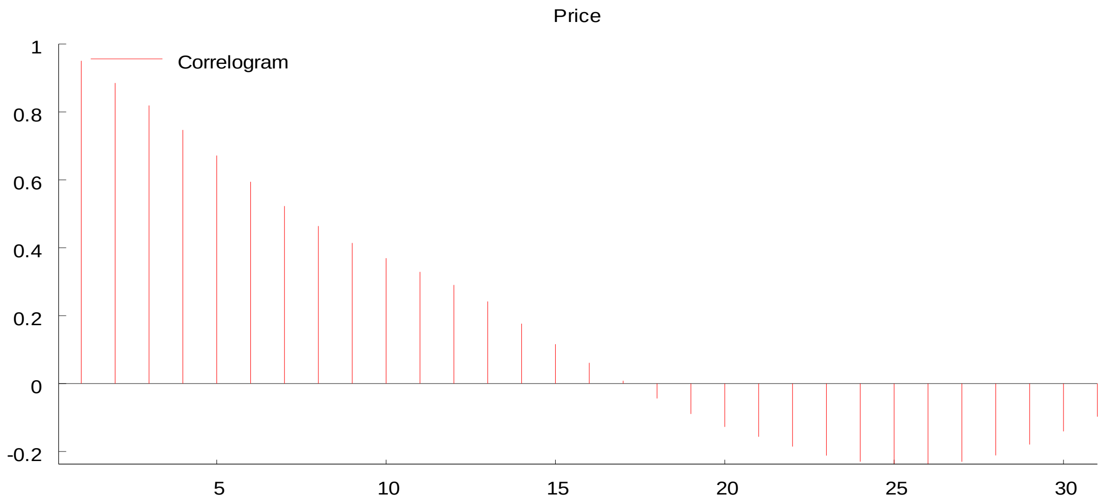


Figure 4: ACF of Diesel Prices

The ACF graph in Figure 4 shows that the autocorrelations decline slowly as the number of lags increase. This is a property of non-stationarity. To achieve stationarity in the series, we difference the data and the find its log and plot the new ACF.

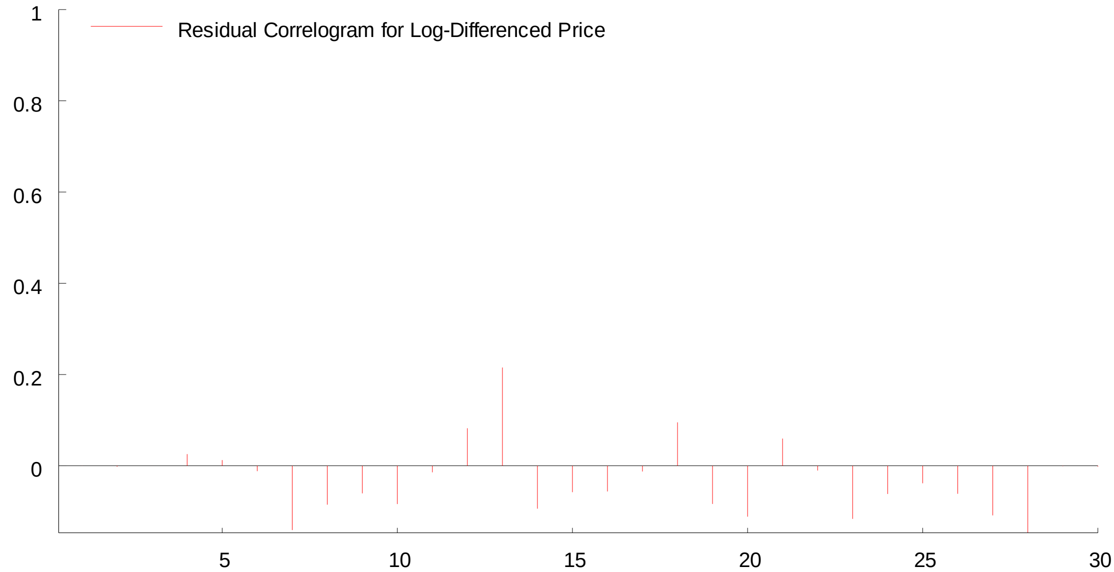


Figure 5: ACF of Log-Differenced Prices

Figure 5 shows the ACF of the transformed data. The autocorrelations here resemble white noise. This is a property of a stationary series. By log differencing the diesel prices, stationarity of the prices was achieved.

Estimation Results

Modeling results that have been estimated using Ordinary Least Square (OLS) method are represented in Table 2.

Table 2

Results of Estimation

Dependent variable: Diesel Prices

Variable	**Estimate**	**Std. Err**	**t Ratio**	**p-Value**
Intercept	0.0038	0.00359	1.059	0.293
AR1	0.33804	0.30626	1.104	0.273
AR2	0.01455	0.26914	0.054	0.957
MA1	0.09682	0.26925	0.36	0.72
MA2	0.08861	0.16544	0.536	0.594

The results on Table 2 show the coefficient estimates of various Autoregressive and Moving Averages schemes of diesel prices in Kenya. All coefficients are not statistically significant at 5% level of significance.

Comparison with Other ARIMA models

The above model was compared with other models and using a model selection criterion that includes Log Likelihood, Schwarz criterion, Hannan-Quinn criterion, Akaike criterion, Residual

Skewness, Residual Kurtosis, and Jarque Bera test. The best model is the one that displays lessor figures of the above named criterion. ARIMA (2,1,2) outperforms the other competing models as presented in Table 3.

Table 3
Comparison of various models

	AR (1,1,0)	**MA (0,1,1)**	**ARIMA (1,1,1)**	**ARIMA (2,1,1)**	**ARIMA (2,1,2)**
Log Likelihood	-152.40	-152.47	-150.79	-148.65	-148.22
Schwarz Criterion	- 147.88	-147.96	-141.77	-137.40	- 136.97
Hannan-Quinn Criterion	-149.38	-149.46	-144.76	-141.13	- 140.70
Akaike Criterion	-150.40	-150.48	-146.79	-143.65	- 143.22
Residual Skewness	-3.11	-3.03	-3.33	-3.32	-3.07
Residual Kurtosis	22.91	22.39	23.48	23.25	22.39
Jarque Bera test	1667.32	1582.00	1758.95	1702.80	1718.66
MSE	0.00208	0.00208	0.00208	0.00209	0.00208
Ljung-Box Q(12)	4.6532	4.6259	4.6570	5.0422	4.8363
Ljung-Box Q squared (12)	0.9583	0.9702	0.9760	0.8563	0.9744
Durbin Watson Statistic	1.99956	1.99955	1.99984	1.97818	1.99518

The Suitable Model

The best model is the one with lowest information criteria. The ARIMA (2, 1, 2) model displays lessor results compared to the others and is hence the best model to forecast the Kenyan diesel monthly prices. Based on estimation results presented on Table 2, the model can be written as follows:

$$Y_t = 0.0038 + 0.33804X_{t-1} + 0.01455X_{t-2} + 0.09682\varepsilon_{t-1} + 0.08861\varepsilon_{t-2} + \varepsilon_t \qquad (21)$$

Diagnostic Checking

The model was tested for normality.The statistics used to test this are Jarque-Bera statistic,residual Skewness, residual kurtosis and the normal QQ plot. The Jarque-Bera statistic (1718.66) rejected the null hypothesis of normality in the residuals in the series. For normality condition in a series, the residual kurtosis and Skewness should be zero; however this is not the case in the results obtained here. The series has a negative Skewness implying that most of the observations are to the left of the normal distribution.

Another condition for normality is that the observations in the series should be along the normal curve if the normal QQ plots were plotted. The normal QQ plots are represented in Appendix 1. The observations in this case do not lie along the normal curve. From the results obtained in this statistics, it is evident that the series is not normally distributed.

Model efficiency was evaluated using MSE. The MSE for the various models are represented in Table 2.From the results, it is clear that AR (1,1,0), MA (0,1,1), ARIMA (1,1,1), ARIMA (2,1,1) and ARIMA (2,1,2) are all equally efficient in modelling volatility of the diesel prices based on MSE.

Model adequacy was tested using the Ljung-Box Q(12) for residuals and Ljung-Box Q(12) statistics for squared residuals. Both the residuals and the squared residuals were not significant at 5% level implying that the models were adequate.

Model independence was assessed by inspecting the sample autocorrelations of the residuals to see if they would resemble the white noise. Figure 5 shows that the residuals approximate white noise and hence the model was independent.

Durbin Watson Statistics were used to evaluate the series for positive or negative autocorrelation. For a series to be free of positive or negative autocorrelation, the Durbin Watson Statistic should be equal to 2.The statistic in this case are very close to 2 and hence no positive or negative autocorrelation in the series.

Forecasting

A five month forecasting of the diesel prices was performed using ARIMA (2,1,2).The results of the forecasts and their respective standard errors are shown in Table 4.Time plots showing the forecasted prices have been shown in appendix 2.

Table 4

Forecasted Prices

Month	Price	Std.errors
July 2012	97.436	3.9710
August 2012	96.933	6.1205
September 2012	96.473	7.6229
October 2012	96.041	8.7332
November 2012	95.635	9.6066

Table 4 shows the general trend of the forecasted diesel prices. In the month of July, the forecasted price was sh.97.436.There was a very small increase in the price from June which was sh.97.94 as shown in appendix 2 .The forecasted price dropped in August to 96.933 and the decreasing trend of the forecasted prices has continued for the next three months until November when the price was sh.95.635.

Conclusion and Recommendation

Conclusion

From the findings the study shows that diesel prices have non constant mean and variance implying that it is non-stationary, thus suggesting the utilization of a non-linear model and implying that diesel prices are not stable and keep on fluctuating unexpectedly. The study concludes that Autoregressive Integrated Moving Average (ARIMA, 2.1.2) was a suitable and valid model to predict volatility and forecasting of the prices of diesel in Kenya. The forecasts obtained indicate a rising trend of the diesel prices for the five months.

Recommendation

From the findings and conclusions the study recommends that the Energy Regulatory Commission should adopt a stable form of diesel prices that are low. The diesel prices in Kenya are characterised by unstable prices that fluctuate unexpectedly. This makes it difficult for diesel fuel users to make informed buying and selling patterns. This is a form uncertainty in the energy market. By the government through ERC ensuring stable prices, the users will be in a better position to make proper buying and selling patterns.

Diesel fuel is one of the inputs used in many sectors for production. High diesel prices may lead to high cost of production and the effect of this is cost push inflation. Inflation is an economic evil as it lowers the value of the currency in terms of other currencies such that

country's exports become expensive while its imports will be cheaper. The country will thus experience more imports compared to exports. The overall effect of this is a terms of trade deficit in the economy. With the government maintaining low prices, such kind of evils will be eliminated and the economy will be in a position to have significant economic growth and development.
From the findings of the study, there is need for comparison of ARIMA modelling of diesel prices and Generalised Autoregressive Conditional Heteroscedasticity (GARCH) and ascertaining which of the two models is the best in analysing the volatility of diesel prices in Kenya.

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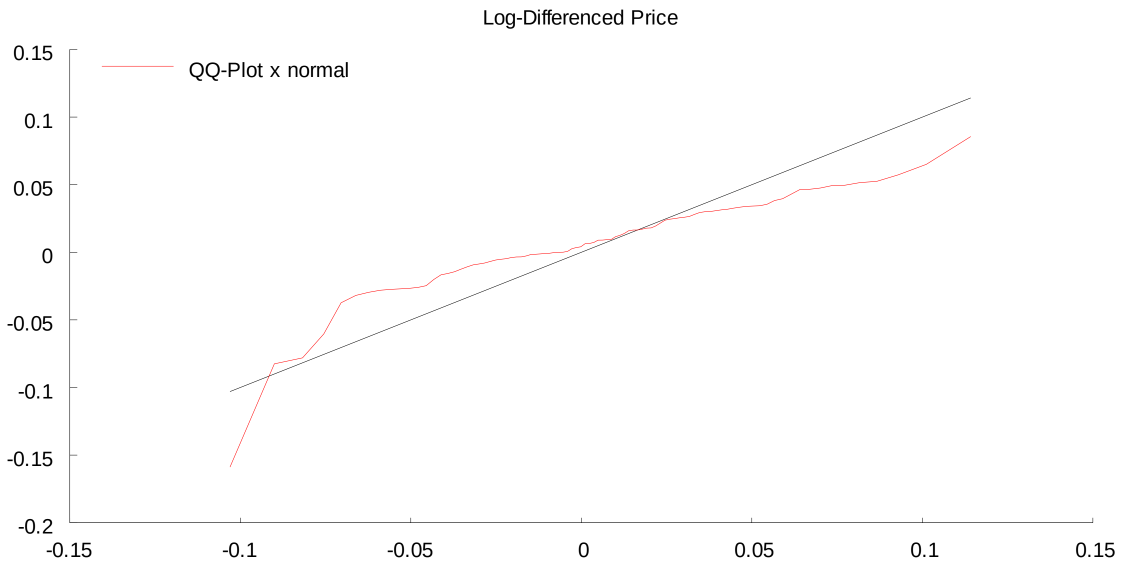
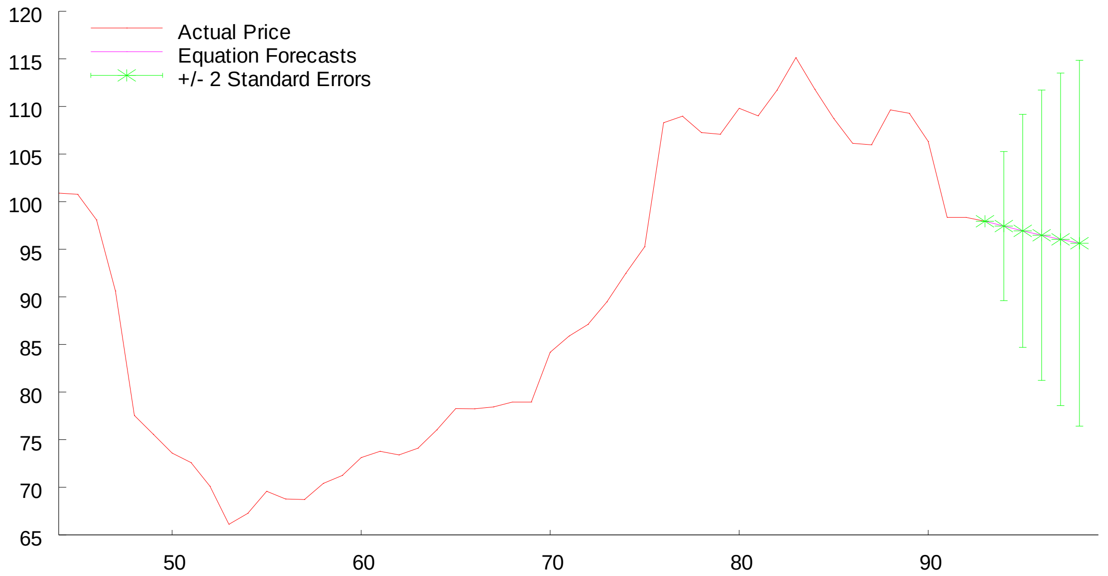
Appendices

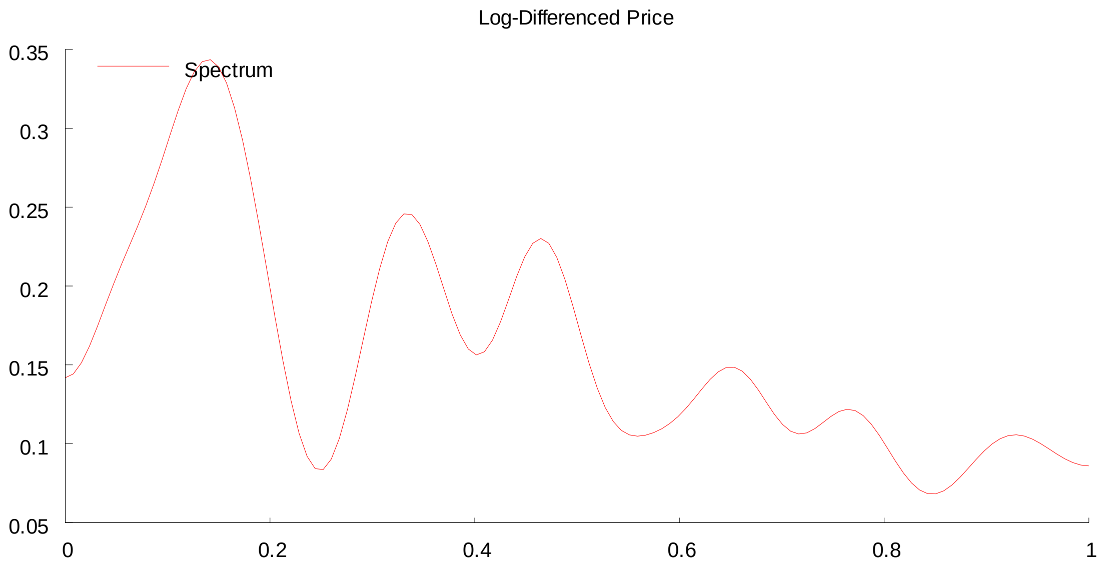
Appendix 1: Normal Plot



Appendix 2: Forecasted Prices



Appendix 3: **Spectrum of Diesel Prices**



Appendix 4: Histogram of diesel Prices