CHAPTER ONE

1.0 INTRODUCTION

1.1 Background of the Study

The menace of crime across the globe is a serious concern. Crime is a known word peculiar to every nations, societies and communities around the world. The West African sub-region and in particular Nigeria is not an exception. One of the teething problems confronting the country is the rising waves of crime. An adage in Yoruba says; “Ilu ti kosofin; ese osi nibe”. This means that, there is no crime, where law does not hold! We can infer therefore that, where there is law, there is crime. Law and other is a defined ways by which nation’s controls crime in the society.

Crime does not have any boundary. It has nothing to do with a country being developed, developing or under-developing. In fact, worst crimes are reported daily in the news in most developed countries of the world. Crime therefore varies across continents and it prevalence can be nation’s characterized. We mean that, some crimes are peculiar with some nations, communities and societies. For instance, kidnapping, Homicides, Armed robbery and killing involving the use of armed weaponry are peculiar in most advanced countries. Suicide bombing, Rape, Homicides, Religion crime and Massacre are peculiar in the Arab nations. Kidnapping, Ethnic fight, Theft, Assault, Tribal war, Corruption, Rioting Religion clashes etc., are peculiar in Africa, etc.

Criminal offences simply put are those behaviors or attitudes that are punishable by law. *Okoro et.al, 2012* opined that a criminal offence is a crime against the state. It can also be called ‘breaking the law’. If you are accused of a criminal offence, the charge sheet will say what offence you have been charge with. Generally in Nigeria, the level of crime offences has risen sporadically. This may be caused by a host of factors. Crime rate in different states are not on the same level, there are states where the level of crime is higher than others. According to the Nigeria Police Force, crime rate in Nigeria has risen geometrically overtime. Crime is an inhibitor to the economic, political and social progress of a nation and a major factor for under-development; this is because it discourages both local and foreign investments, reduces the quality of life of its citizens and damages relationship between citizens and states, thus undermining democracy, the rule of law and the ability of the country to promote sustainable development and peace (Abayomi 2013).

Kwara State of Nigeria is the only State we will focus our study on. In classifying crimes, crime do varies even within States of a nation. For instance, in Nigeria today (2003 – till date), Bombing, Terrorism, Suicide bombing, Religion war & killing, Vandalism etc., is a crime peculiar in the Northern part of Nigeria particularly in the states like Borno, Adamawa, Kano and Yobe whereas, Kidnapping, Pipeline vandalism, Armed robbery and Oil theft are order of the day in Niger-Delta part of Nigeria. In the South west and in the Eastern part of Nigeria, we have heard of cases of Ritual killing, Theft &Stealing, Kidnapping, Assaults, Wounding, Armed robbery etc. This simply implies that, crime prevalence may varies across borders but there is no society, community or nation that is void of crime.

Crime prevention which can be the measures designed to eliminate or refused the prospect that an individual who has not previously had frequent or serious encounters with law enforcement agencies will engage in behavior that may eventuate being processed as a criminal. There are various methods practiced here in Kwara State by the Police to curb crimes which are classified into motorized patrols, detection, prosecution, physical protection method etc. Police as an arm of judiciary which is responsible for law enforcement in Nigeria societies, their main objectives is to ensure perfect public peace within Nigeria.

1.2 BACKGROUND TO THE STUDY

Crimes become a national or community problems when it is chronic and systematic and its coincidence, pattern and seriousness become a threat to the general wellbeing of people. There are four indicators of whether or not a country or state has crime problem. These indicators are; the extent, seriousness, pattern and the control capacity or effectiveness of crime control institutions. Based on this fact, we can boldly say "Nigeria has a crime problem"

In recent times, armed violence has taken several forms in most of the states of the North Central region of Nigeria which kwara state is an active member. Between 2012 and 2013, armed robbers attacked banks in both share and Omu-Aran, headquarter of Ifelodun and irepodun Local Government Area respectively leaving scores of people dead with an unimaginable degrees of injuries to others. This eventually led to the closure of banks in Omu-Aran exposing the residents of the ancient town and its environs to danger of keeping money at home.

In December 19th 2013, Offa was thrown into pandemonium as armed bandits reportedly numbered up to 30 stuck the town and invaded four commercial banks in the town. The operation which was said to have lasted for about two hours also rendered 10 policemen, 16 civilians dead and several sustained brutal injuries with several millions of naira carted away by the hoodlums (**Weekly trust newspaper, 21st December, 2013).**

Since this incident, residents of Offa, Omu-Aran, Share have been battling with fear of another attack. The fear of attack spread to Ilorin, the state capital, as banks in Ilorin throughout December/January 2013 and 2014 respectively were rendering skeletal services to their customers in a bid to minimize their possible losses in the event of an attack.

In the new dimension of recent violent attacks, it has been observed that police stations and other security institutions in the target locations are the first aims of the attacks before proceeding to their (attackers) core businesses of the day. This is aimed at ensuring disturbance free operations by bandits. In the last Offa robbery, the robbers were reported to have firstly unleashed their venoms on Owode Police Divisional Station leaving about 13 police officers dead and set inmates of undisclosed numbers free.

The increasing in numbers of prison inmates in Kwara State between the years 2003 to 2007 also poses alarming security situations in the state. The cost of injustice and insecurity clearly override and in most cases blot out the gains of development even over decades or centuries.

In development language, more secured states of the world enjoy more rapid and a sustainable development than those involved in crimes of various dimensions. In other words, neither investment nor any investor interested in crime centered states or zones as such development may rather lead to capital fight in lieu of direct inflow of investment. The loss of zones or states in crises is often added to gains of regions or states in relative peace. This can be viewed from the stand of Kwara State Government in November, 2013 to stand up against crime incidence in the state while flagging off what it tagged "**Operation Harmony"** aimed at strengthening the security operatives across the state and bring crime under reasonable control.

In this regards and following the above connection between crimes, security, peace on one hand and socio-economic development on the other, having knowledge of crime status of the immediate environment (State) where we live is not only important but beneficial.

1.3 HISTORICAL BACKGROUND OF KWARA STATE

Along with Benue and Plateau, Kwara was created forty five (45) years ago as one of the 12 states of the federation. Nasarawa and Kogi were later developed in the creation of states within the geo-political unit known as North-Central zone (NCZ) in Nigeria which is the fourth zone with the population of 20.4millions of the whole 140.4millions of population (2006 census)

Kwara state occupies 35705sq kilometers and accounted for 15.61 percent of the zonal land area. From 2006 census figure, the state is the home of 2.36million persons out of the 20.4million population of North-Central zone. Kwara state is made up of only sixteen out of the 120 local government Areas in the zone, this is representing 13.33 percent of the entire local government areas in the zone.

1.4 AIM AND OBJECTIVES

This research work which is concerned with theft and assault is aimed to fit an appropriate time series model. Specifically, the objectives of this research work were to;

i. identify the pattern of crime rates from 2006 through 2015;

ii. develop an adequate time series forecasting model;

iii. check the adequacy of the fitted model; and

iv. forecast for the period of 12 months.

1.5 SCOPE OF THE STUDY

This study is centered on Time Series Analysis of Data on Criminal Offences in Kwara State from 2006– 2015 which is restricted to only Theft and Assault criminal offences in the state. Another scope of the study is to know the frequency of crime committed in Kwara State. Thirdly, estimate the best model of forecast for the future crimes and to check the seasonality of the data. Lastly, forecast for the future of crime for the next 12months.

1.6 SIGNIFICANCE OF THE STUDY

The significance of the project is to provide some knowledge of time series analysis on rate of criminal offences in the state. The study will give insight into the pattern of trend of criminal offences in the state; thereby using that to forecast for the future.

1.7 DEFINITION OF TERMINOLOGIES

Following the breakdown analysis of this project, a better understanding of terms and concept will be used by defining some of the terms in conformity with the legal standard, and they include:

Time Series: A time series is a collection of observation of the same phenomenon made sequentially in time at regular interval (Chatfield, 2000)

Stochastic Time Series: A series whose future values can only be using its probability distribution function. Examples include,; rainfall, productions, sales in successive weeks etc.

Time Plot: The first step into the analysis of time series is to plot the observations against time. This will show important features of the data such as trends, seasonality, outliers etc.

Trends: This is a type of variations when a series exhibits steady upward growth or downward declines over successive periods of time.

Seasonal Variation: This is an identical or almost identical pattern which a series appears to follow as a result of recurring events which take place annually, monthly, weekly, daily, hourly etc.

Autoregressive Processes: This assumes that current values of the series are linearly dependent upon its previous values with some errors. As a result, we could have the linear relationship:

$$X_t = \alpha x_{t-1} + e_t \qquad \text{where } e_t \text{ is a weighted sum of the past white noise}$$

ARIMA: Autoregressive Integrated Moving Average. It is a combination of the two important model {The Autoregressive (AR) and the Moving average model (MA)} above which are differenced in nth times.

Autocorrelation: This is an important feature of times series which measures the linear relationship between observations at different distances apart. These coefficients often provide insight into the probability model which generated the data hence, the sample autocorrelation coefficient is similar to ordinary correlation coefficients between two variables X and Y. Autocorrelation or ACF refers to the correlation of a time series with its own past and future values. Autocorrelation is also sometimes called "lagged correlation" or "serial correlation", which refers to the linear relationship between members of a series of number arranged in time.

Partial Autocorrelation: A partial Autocorrelation of order K measures the strength of correlation among pairs of entries in time series while accounting for or removing the effects of all autocorrelation below order K. For instance, the Partial Autocorrelation coefficients for order K=5 is computed in such a manner that the effects of the k= 1, 2, 3 and 4 partial autocorrelation have been excluded. The Partial Autocorrelation coefficient of any particular order is the same as the auto regression coefficients of same order.

Correlogram: This is a useful graph used in interpreting a set of autocorrelation coefficients. It is plotted against the lag (k). The graph of r_k against K is called sample autocorrelation function (ACF).

CHAPTER TWO

2.0 LITERATURE REVIEW AND METHODOLOGY

2.1 LITERATURE REVIEW

Over the years, many theories have been presented in attempts to define and explain criminal activity. Some of these have focused on individual criminals while others examine the aggregate crime within an area. Although, the public perception may be that crime is randomly distributed in space, extensive evidence now exists that it is not. In this work, we dig into varieties of articles published on crime across the globe in order to have insight and general views of how crimes affect different nations of the world.

The changing picture of crime rates and public attitudes towards crime over time is a complex relationship that may not be fully explained by univariate analysis of crime rates on people's concern for crime. Criminologists, law enforcement agencies, and researchers from many academic disciplines have noticed that the public has maintained the belief that violent crime is out of control despite the fact that crime rates have been steadily declining for years. A 2008 study confirms that despite dramatically decreased crime rates in recent years, the public continues to believe that violent crime rates are out of control (Duffy, Wake, Burrows, & Bremner, 2008). As long as this belief persists, the public tends to blame the government for failing to properly address their beliefs about crime rates and for neglecting to meet their personal safety needs (Duffy, et al. 2008). Researchers, policy makers, and law enforcement officials in the U.S. benefit from awareness of the public's varying relationship with true crime rates. If we can better understand if and when people are making logical decisions about their concern for crime relative to crime rates, we can address how to improve instances of irrationality when people use competing sources of information to learn about crime.

Public perceptions of crime may be swayed by several contributing factors. Felson (2002) contributes a theory for predicting people's concern for crime and attempts to explain why concern for crime and falling crime rates do not always align. Felson's *random crime fallacy* argues that people believe crime is random and unpredictable, while the opposite is more likely true – that crime events are actually predictable.

Nigeria has one of the alarming crime rates in the world "Uche, (2008) and Financial, (2011)", "Uche, O. (2008). Nigeria prison Robbed by Criminals. http://www.which way.nigeria/net/Nigeria-prison-robbed-criminals/". Cases of armed robbery attacks pick pockets, shoplifting and 419 have increased due to increase of poverty among population "Lagos (undated). Pickpockets, shoplifting and 419; http://lagos-nigeria/-real-estate-advisor.com/crime-rate.html" in the year 2011, armed robbers killed at least 12 people and possibly more attack on a bank and police station in North-Eastern Nigeria (Nossiter, 2011, Robbers kill at least 12 in Nigeria August 5, 2011, http://www.nytimes.com/2011/08/26/wor/cd/africa/26nigeria.html?r=1).

On the 9th of March, 2015, CNN reports informed us that USA and UK had already started public orientation and education of their citizens on the danger of joining any terror group. It had already being made a punishable offence and a law. Research has shown that education have a strong negative relationship with crimes. Education has been shown to have a strong negative correlation with crime. Machin, Marie and Vujie (2011a) estimate that 1% point fall in the proportion of males leaving school with no qualifications would reduce property crime by a roughly equivalent amount. No such effect is observed for violent crime. Machin, Marie and Vujie (2011b) study youth crime in more detail, identifying strong crime reducing impacts of education (this time on both property and violent crime). If government can introduce compulsory education for all and sundry in Nigeria, we believe it is a bold step forward to saving the future and avail the future of high crime rates which is obviously visible if plans to curtail are not in place. That is, the higher the number of educated; the lower the crime rates in the societies and vice versa.

2.2 METHODOLOGY

The statistical techniques that are useful for analyzing time series data will be review in this topic. The analysis of time series is based on the assumption that successive values in the data file represent consecutive measurement taken at equally spaced intervals.

2.3 SOURCE OF DATA AND METHOD OF DATA COLLECTION

The data used for this project work was collected from Kwara State Police Command Headquarter, Kwara State. The method employed is secondary method of data collection. Secondary data is a type of data which is already made that is, it has been developed by another person and not by the researcher. The data used in this project work is a monthly data of criminal offences collected on two different criminal acts; (1) THEFT (2) ASSAULT. The sample of study is Kwara State Police Command Headquarter. The data is secondary in nature and covers a period of ten (10) years from 2006 to 2015. The data is restricted to the number of criminal offences recorded at the state command only.

2.4 METHOD OF DATA ANALYSIS

A time series is a collection of observation made sequentially at equal interval of times this is denoted by X_t, where X_t is the observed value at time (t). The fundamental important of time series is that the observations are taken at regular interval of time. These observations are dependent on time and the successive observations are dependent on one another. Time Series Analysis (TSA) involves the degree and pattern of dependent observation X_t.

2.5 NON STATIONARY AND STATIONARY PROCESS

A time series is a record of observation that is time variant i.e. time dependent. These observations are generally by stochastic model which do not hate time invariant structure. Such a time series is said to be stationary. A stationary time series is said to have a constant mean and variance. Also, in the process generating the series, if it is possible to estimate a constant mean and variance, such a process is said to be stationary process Generally, a time series X_t is stationary if it has no trend ($T_t = 0$), no seasonal variation ($S_t = 0$) and no systematic change in its variance. Hence, a time series with only the irregular variation is said to be stationary

On the other hand if the stochastic structure itself changes with time, the series is said to be non-stationary i.e. a non-stationary time series is said to have a time variant mean and variance (i.e. these are function of time (t))

Stationary of time series is however an important property a series must process before it's been estimated as far as timed series analysis is concerned, Jenkins(1976)

2.6 UNIVARIATE TIME SERIES MODELS

As mentioned modeling time series data can be dealt with using either time domain of frequency domain approach. Time domain approach is somehow simpler.

Time domain approach is usually parametric in nature, and is based on direct modeling of the lagged relationship between a series and its past history (past values/lagged values) possible to forecast its future values. The most applied univariate time domain models are given below.

- Autoregressive Model (AR)
- Moving Average model (MA)
- Autoregressive Moving average Model (ARMA) for stationary time series

While for Non-Stationary Time Series, We Have

- Autoregressive Integrated Model (ARI)
- Integrated Moving Average (IMA)
- Autoregressive Integrated Moving Average (ARIMA)

All the models mentioned here are for linear time series data. But for this project we shall be using the ARIMA time series model for data of babies admitted since the model of the data have been identified using the ACF(Autocorrelation function), PACF (partial autocorrelation function, Correlogram Some Univariate Stationary Models in Time Series

Given a finite number of observation, (X_t) we can construct a finite order parametric model to describe a time series process. Several dynamic models that are linear stationary time series model are AR (q) and ARMA (p,q) models

1. **Autoregressive Process AR(p)**

A stationary time series (X_t) is said to be an autoregressive process of order p if it satisfies

$$X_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + \varepsilon_t \dots\dots\dots\dots (2.1)$$

Where $\emptyset_{1,}\emptyset_2 \dots, \emptyset_p$ are autoregressive parameters and $\{\varepsilon_t\}$ is a white noise process with mean zero and constant variance δ^2Equation (3.1) can be re-written as

(1-$\emptyset_1 B - \boldsymbol{\emptyset_2 B^2} - \cdots - \boldsymbol{\emptyset_{tB_t}}) X_{\boldsymbol{t}} = \varepsilon_{\boldsymbol{t}} \dots\dots..$ (2.2)

And this implies $\Phi(B)X_{\boldsymbol{t=\varepsilon_t}}$ ………… ….. (2.3)

Where Φ(B) is a polynomial in B. For stationarity the roots of (B) must lie outside the unit circle i.e |B|> 1.

2. **Moving Average Process MA(q) Process**

A stochastic process $\{X_t\}$ is said to be a moving average process of order (q) if it satisfy the different equation.

$$X_t = \varepsilon_t + \emptyset_1 \varepsilon_{t-1} + \emptyset_2 \varepsilon_t + \cdots. + \emptyset_p \varepsilon_{t-p} \dots\dots\dots\dots. (2.4)$$

For MA(q) the invertibility condition holds.

3. **Autoregressive Moving Average (ARMA) process**

We can express AR (1) as an MA(∞) can be expressed as an AR(∞). Hence to have a minimum number of parameters, it is then logical to describe a system by as few parameters as possible by expressing a tune series model as a combination AR and MA processes, called an autoregressive moving average process (ARIMA) model.

Thus a stationary process $\{X_t\}$, satisfy an ARIMA (p,q) process if

$$X_t - \emptyset_i X_{t-1} - \cdots - \emptyset_q X_{t-q} = \varepsilon_t - \theta_i \varepsilon_{t-q} - \cdots - \theta_p \varepsilon_{t-q} \dots\dots (2.5)$$

Where $\{\varepsilon_t\}$ is a white noise process with var $(\varepsilon_t)= \sigma^2$ Equation (2.5) can be expressed as;

$$\Phi(B)X_t = \theta(B)\varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{(2.6)}$$

Where we have that $\Phi(B)(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p)$

For stationary, we require the root of the characteristics equation Φ

$(B) = 0$ to lie outside the unit circle and the condition for invariability is that the roots of the characteristic equation B)=0 lie outside the unit circle.

4. Auto Regressive Integrated Moving Average (ARIMA)

The ARIMA methodology was proposed by Box (1976), and it is now a quite popular tool in economic forecasting. The basic idea is that a stationary time series can be modeled as having both an autoregressive (AR) and a moving average (MA) component Non-stationary integrated series can also be handled in the ARIMA framework, but it has to be reduced to stationary beforehand by differencing the data. The multiplicative ARIMA representation can be written as

$$\Phi_p(L)(1 - L^s)^{\mathrm{D}}(1 - L^s)^{\mathrm{d}} y_t = \delta + \theta_q(L)\theta_q L(\varepsilon_t) \dots\dots\dots \text{(2.7)}$$

Where$\Phi_p(L), \phi_p(L) and \theta_q(L)$ are polynomials in the lag operator (L), d and D are the number of consecutive and seasonal differences needed to make the series stationary, p, p,q and Q are the degrees of the autoregressive and moving average polynomials and ε_t is a normally distributed random error with zero mean and constant variance. The model is multiplicative in the sense that the; observed data result from the successive filtering of a random noise (ε_t) through the non-seasonal filter $(f_p(L))$ and then the seasonal filter (FP(L)). The model is given as;

$$X_t = \sum_{i=i}^{P} \emptyset_t X_t + e_t - \sum_{j=i}^{q} \theta_t e_{t-j} \dots\dots\dots \dots.. \text{(2.8)}$$

Where $\phi_{1,} \phi_{2,} \dots \phi_p,\ \theta_1 \theta_2, \dots., \theta_{p,}$ are parameters tobe estimated, X_{t-1} are the lagged values of the series, $\varepsilon_{t-1}$and are the lagged values of the white noise process?

The modeling procedure can be divided in three parts. In the first stage, the order of differencing and the degrees of the AR arid MA polynomials are determined using both the estimated autocorrelation and partial autocorrelation functions. In the second stage, the parameters (*f,* F q and Q) are estimated and several tests are performed to assure that the residuals are white noise. Likelihood methods are generally used for estimation purposes, but if the model has only an AR part least squares estimation will be appropriate. Finally, in the third stage, the best most parsimonious model is used to obtain the forecasts. The likelihood function stationary model can be written as

$$L(\phi,\theta,\delta^2/y_t) = (2\pi)^{-T/2}(\delta^2)^{-T/2}exp[(-\frac{1}{2\delta^2})\sum e^2] \text{ .... } (2.9)$$

Identification of ARIMA Models

The objective of the identification is to select a subclass of the family of ARIMA models appropriated to represent a time series. We follow a two-step procedure: first, get a stationary time series, that is, we select the parameter λ of the Box-Cox transformation and the order of integration d, and secondly we identify a set of stationary ARIMA processes to represent the stationary process, that is, we choose the orders (p, q)

2.7 SELECTION OF STATIONARY TRANSFORMATIONS

Our task is to identify if the time series could have been generated by a stationary process. First, we use the time plot of the series to analyze if it is variance stationary. The series departs from this property when the dispersion of the data varies along time. In this case, the stationary in variance is achieved by applying the appropriate Box-Cox transformation and as a result, we get the series$y_t^{(\lambda)}$

The second part is the analysis of the stationary in mean. The instruments are the time plot, the sample correlograms and the tests for unit roots and stationary. The path of a non-stationary series usually shows moves around a unique level along time. The sample autocorrelations of stationary processes are consistent estimates of the corresponding population coefficients, so the sample correlograms of stationary processes go to zero for moderate lags. This type of reasoning does best and most the non-seasonal not follow for non-stationary processes because their theoretical autocorrelations are not well defined. But we can argue that a non-decaying behavior of the sample ACF should be due to a lack of stationary. Moreover, typical profiles of sample correlograms of integrated series are shown in figure 3.7 the sample ACF tends to damp very slowly and the sample PACF decays very quickly, at lag j=2, with the first value close to unity.

When the series shows non-stationary patterns, we should take first differences and analyze, if $\Delta y_t^{(\lambda)}$ is stationary or not in a similar way. This process of taking successive differences will continue until a stationary time series is achieved. The process of taking successive differences will continue until a stationary time series is achieved. The graphics methods can be supported with unit-root and stationary tests. As a result, we have a stationary time series $z_t = \Delta y_t^{(\lambda)}$ and the order of integrated will be the number of times that we have differenced the series $y_t^{(\lambda)}$.

2.8 SELECTION OF STATIONARY ARMA MODELS

The choice of the appropriate (p,q) values of the ARMA model for the stationary series z_t, is carried out on the grounds of its characteristics, that is, the mean, table 2.1 below present the autocorrelation pattern of the ACF and PACF of ARMA process

Table 2.1 showing the Autocorrelation patterns of ARMA process

Process	ACF	PACF
*(2mm) AR(p)	Infinite exponential and/or sine-cosine wave decay	Finite: cut off at lag P
MAq)	Finite: cut off at lag P	Infinite: exponential and/or sine-cosine wave decay
ARMA(p,q)	Infinite: exponential and/or sine-cosine wave decay	Infinite: exponential and/or sine-cosine wave decay

The mean of the process is closely connected with the parameter λ: when the constant term is zero, the process has zero mean. Then a constant term will be added to the model if $H_0: E(z) = 0$ is rejected

The orders (p, q) are selected comparing the sample ACF and PACF of z_t with the theoretical patterns of ARMA processes that are summarized in table 2.1

2.9 PARAMETER ESTIMATION

The parameters of the selected ARIMA (p,d,q) model can be estimated consistently by least-squares or by maximum likelihood. Both estimation procedures are based on the computation of the innovationsε_t from the values of the stationary variable. The least-squares methods minimize the sum of squares,

$$min \sum_t \varepsilon_t^2 \text{......... ....} \quad (2.10)$$

The log-likelihood can be derived from the joint probability density function of the innovations$\varepsilon_1 \dots \dots \varepsilon_t$, that takes the following form under the normality assumption,

$$\int (\varepsilon_t \dots \dots .. \varepsilon_T) \propto \sigma_\varepsilon^{-T} exp\{-\sum_{t=1}^{T} \varepsilon_t^2 / 2\delta_\varepsilon^2\} \text{......... .....} \quad (2.11)$$

In order to solve the estimation problem, equations (2.8) and (2.9) should be written in terms of the observed data and the set of parameters (θ,Φ, δ). An ARMA(p, q) process for the stationary transformation z_t can be expressed as:

$$\varepsilon_t = z_t - \delta - \sum_{i=1}^{p} \emptyset_{i\, z^{j-i}} - \sum_{b}^{t=1} \theta^i \varepsilon^{i-j} \text{......... .....} \quad (2.12)$$

Then, to compute the innovations corresponding to a given set of observations $(z_1 \dots .. z_t)$ and parameters, it is necessary to count with the starting values$z_0 \dots, .. z_{p-1}$, $\varepsilon_0 .., .., \varepsilon_{q-1}$. More realistically, the innovations should be approximated by setting appropriate conditions about the initial values, giving to conditional least squares or conditional maximum likelihood estimators.

In the case of computing more models we choose the model where AIC (Akai information criteria), respectively SBC (Schwartz-Bayes criteria) are minimal and Log likelihood is maximal. At the end we verify if the residual component is the white noise. In ARIMA models, we assume dependence between the quantities *yt*-2 *, yt*-1*, yt , yt*+1*, yt*-2 *,...*

If this process contains the seasonal fluctuation, as it is in this model, we can expect also the dependence seasons: *yt*-2*s* , *yt*-*s* , *yts* , *yt* +*s* , *yt* +2*s* ,..., where *s* is the length of the period (in this case 12).

This process is called SARIMA (*p,d,q*) (*P,D,Q*)s , where

p is order of process AR, *q* is the order of process MA, *d* is the order of difference, *P* is order of seasonal process AR, *Q* is the order of MA, *D* is order of seasonal difference, *s* is the length of seasonal period.

The general *SARIMA*(*p*,*d*,*q*)(*P*,*D*,*Q*)*m* process *Xt* is the solution of the following equation

$\Phi(B^m)\phi(B)\nabla_m^D\nabla^d \mathrm{Xt}=\Theta(B^m)\theta(B)Zt$……. ….. (2.13)

Where

$\nabla \mathrm{mXt}=Xt-Xt-\mathrm{m}$……. ….. ……………. (2.13a)

$\nabla Xt=\mathrm{Xt}-\mathrm{Xt}-1$……. …………………… (2.13b)

$\Phi(B^m)=1-\Phi 1\mathrm{Bm}-\cdots-\Phi \mathrm{PB}^{\mathrm{PM}}$……. ….. (2.13c)

$\phi(B)=1-\phi 1B-\cdots-\Phi B$……. ….. ………… (2.13d)

$\Theta(B^m)=1+\Theta 1\mathrm{B}^{\mathrm{m}}+\cdots+\Theta \mathrm{QB}^{\mathrm{Qm}}$……. ….. (2.13e)

$\theta(B)=1+\theta 1B+\cdots+\theta \mathrm{qB}^{\mathrm{q}}$……. …………….. (2.13f)

and $B^n Xt=Xt-n$……. …………………… (2.13g)

$\phi(B)$ is autoregressive operator, $\theta(B)$ is the operator of moving averages, $\Phi(B^m)$ is seasonal autoregressive operator, $\Theta(B^m)$ is seasonal operator of moving averages, *Zt*, is white noise.

2.10 DICKEY FULLER (DF) UNIT ROOTS TESTS

The Dickey–Fuller test involves fitting the regression model Δyt = ρyt−1 + (constant, time trend) + ut (1) by ordinary least squares (OLS), but serial correlation will present a problem. To account for this, the augmented Dickey–Fuller test's regression includes lags of the first differences of yt.

We have not dealt with it, but the Dickey Fuller test produces two test statistics. The normalized bias T (π− 1) has a well defined limiting distribution that does not depend on nuisance parameters it can also be used as a test statistic for the null hypothesis H0: π = 1. This is the second test from DF.

Here a formal procedure of testing for non-stationary/unit root is presented.

Let $Y_t = \rho Y_{t-1} + \varepsilon_t$……. ….. (2.14)

And $\Delta Y_t = \alpha Y_{t-1} + \varepsilon_t$; ……. ….. (2.15)

Where $\alpha = \rho - 1$ and$\Delta Y_t = Y_t - Y_{t-1}$, where Y_t is the exchange rate at time t.

If $\alpha = 0$, then $\rho = 1$, that is we have a unit root, meaning the time series under consideration is nonstationary. But if $\alpha < 0$, then $\rho < 1$, meaning the time series under consideration is stationary.

The appropriate hypothesis for conducting Dickey-Fuller Tests is as follow

Null hypothesis, H_0: The series is not stationary

Alternative hypothesis, H_1: The series is stationary

DECISION RULE: Reject H_o if P-value is less than $\alpha = 0.05$.

2.11 DIAGNOSTIC TEST OF RESIDUALS

After selection of the best model the following diagnostics of the residuals are made:

Time of the Residuals: Time plot of the standardized residuals should not show any structure. It must indicate no trend in the residuals, no outliers and in general case no changing variance across time.

Plot of ACF: Once the appropriate ARIMA model has been fitted, one can examine the goodness of fits by means of plotting the ACF of residuals of the fitted model. If most of the sample autocorrelation coefficients of the residuals are within the limits where N is the number of observations upon which the model is based then the residuals are white noise indicating that the model is a good fit.

Testing the Model Adequacy: After identifying the appropriate model for a time series data, it is very important to check the adequacy of the model. The error terms are examined; for the model to be adequate, the error should be random. If the error terms are statistically different from zero, the model is not considered adequate.

The test statistic used is the Ljung-Box statistic, also called modified Box-Pierce statistics, is a function of the accumulated sample autocorrelations, r_j, up to any specified time lag m. As a function of m, it is determined as:

$$Q(m) = n(n+2)\sum_{j=1}^{m} \frac{rj^2}{n-j} \text{ .... } (2.16)$$

Which is approximately distributed as X^2 df = nq-p, where p & q are orders of AR and MA respectively and n= number of usable data points after any differencing operations.

CHAPTER THREE

DATA PRESENTATION AND ANALYSIS

3.0 INTRODUCTION

Data for the study were collected on monthly basis from Kwara Police Command Headquarter, Kwara State for the period January 2006 – December 2015. It covers the number of criminal offences in Kwara State; mainly Theft and Assault criminal offences.

Considering that the data is a time-sequence data collected at regular interval (monthly), we would adopt the technique of time series analysis in analyzing the data. Descriptive statistics would also be used to summarize the data.

3.1 PRESENTATION OF DATA ON THEFT CRIMINAL OFFENCE

Table 3.1 showing monthly data on Theft Offence in Kwara State from 2006 to 2015

YEAR/ MNTHS	JAN	FEB	MA RCH	APRIL	MAY	JUNE	JULY	AUG	SEPT	OCT	NOV	DEC
2006	57	43	19	32	23	54	49	33	37	0	0	28
2007	25	28	1	10	32	29	25	43	7	1	4	0
2008	27	28	29	30	38	28	44	49	45	43	44	70
2009	55	65	41	44	43	40	34	40	64	29	24	45
2010	32	35	21	24	35	30	23	23	23	26	17	17
2011	25	31	18	25	31	25	27	19	24	26	17	20
2012	14	14	23	17	21	13	17	19	24	12	7	12
2013	22	9	12	15	13	11	11	15	14	14	12	24
2014	14	14	15	20	19	16	13	7	15	16	14	23
2015	7	8	13	17	12	18	14	14	17	16	13	8

SOURCE: Kwara State Police Command Headquarter

Table 3.1 above shows the recorded number of theft offence in Kwara State from which the highest value was recorded in the month of February 2009 while the lowest record was done in the month of March and October respectively in the year 2007; yet, months like October and November, 2006 do not have any record for theft offence in Kwara State. 2007 has the smallest record of theft in the state while 2009 has the highest record.

TIME PLOT GRAPH FOR THEFT OFFENCE

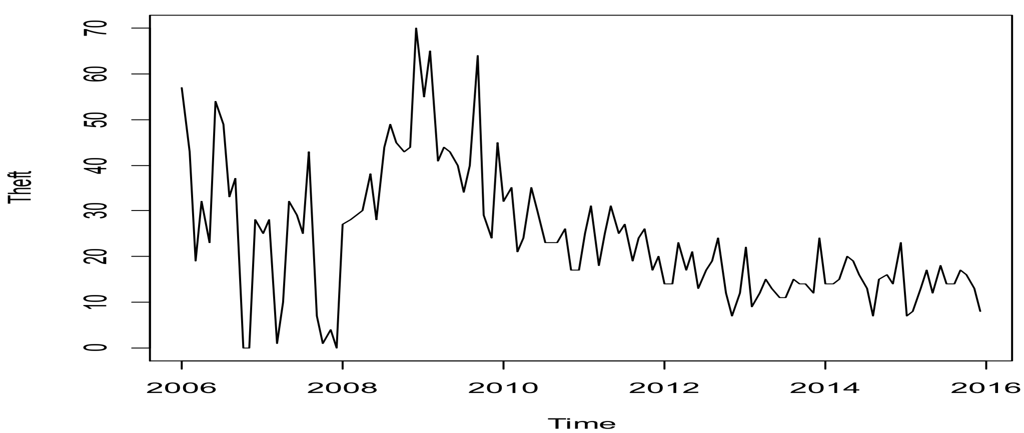

Fig 3.1: Time Plot Graph for Theft Offence

Fig 3.1 above shows the pattern of movement for the data on Theft criminal offences; and hence there will be a need to test for the stationary of the data.

UNIT ROOT TEST OF STATIONARY

Table 3.2 DICKEY-FULLER TEST FOR THEFT OFFENCE

Dickey fuller
Augmented Dickey-Fuller Test
data: Theft
Dickey-Fuller = -2.2204, Lag order = 4, p-value = 0.485
alternative hypothesis: stationary

The appropriate hypotheses for conducting Dickey-Fuller Tests are as follows:

Null hypothesis, H_0: There is no stationarity

Versus

Alternate hypothesis, H_1: There is stationarity

By adopting the conventional Decision Rule, the decision arising from the entries in Table 3.2 is since p-value (0.845) is greater than the significant level; α(= 0.05);

Hence the appropriate conclusion for the dataset is that it is not stationary at 0.05 level of significant. The consequence of this conclusion is that the condition of stationarity has not been affirmed, and therefore there is need to perform differencing.

DIFFERENCED DATA ON THEFT FIRST TIME

TIME PLOT GRAPH SHOWING THE DESCRIPTION OF THE DIFFERENCED DATA ON THEFT CRIMINAL OFFENCE

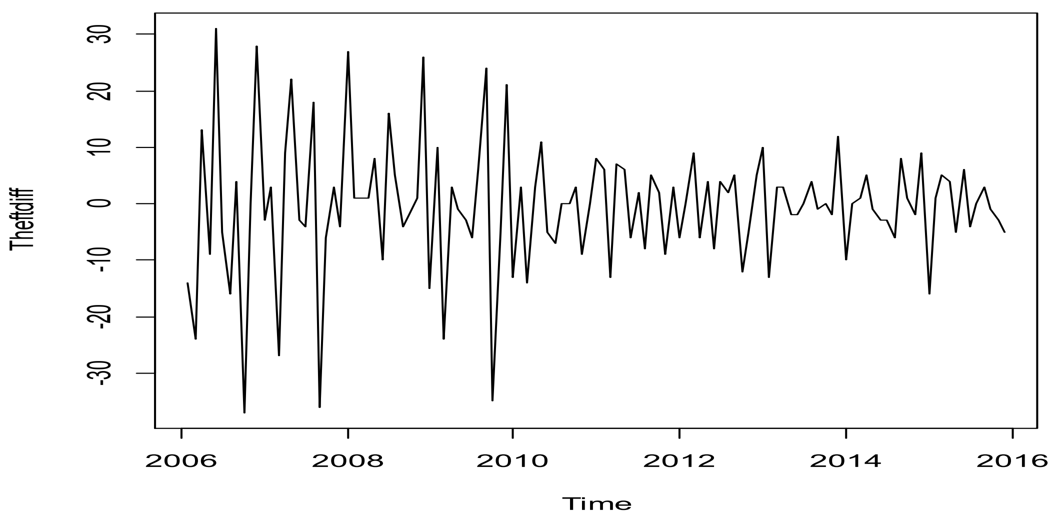

Fig 3.2 Time Plot Graph for Differenced Data on Theft Criminal Offence

Fig 3.2 shows that the pattern of movement of the differenced data and therefore test for stationary is required.

UNIT ROOT TEST OF STATIONARY

Table 3.3 DICKEY-FULLER TEST FOR THE DIFFERENCED DATA

Augmented Dickey-Fuller Test
data: Theftdiff
Dickey-Fuller = -7.0184, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

The appropriate hypotheses for conducting Dickey-Fuller Tests are as follow:

Null hypothesis, H_0: There is no stationarity

Versus

Alternative hypothesis, H_1: There is stationarity

By adopting the conventional Decision Rule, the decision arising from the entries in Table 3.3 is since p-value (0.01) is less than the significant level, $\alpha(= 0.05)$;

Hence the appropriate conclusion is the dataset is stationary at 0.05 level of significant. The consequence of this conclusion is that the condition of stationarity has been affirmed, and therefore there is no need to perform any form of differencing.

SEASONAL DECOMPOSITION CHART FOR THEFT OFFENCE

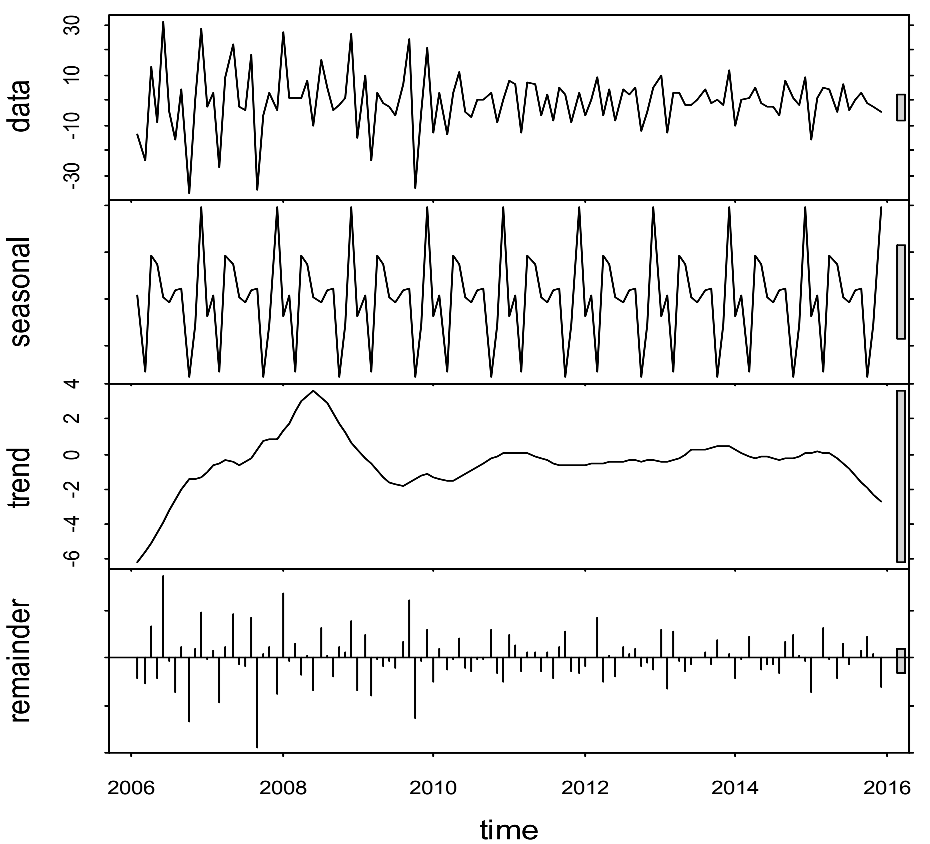

Fig 3.3 Show the seasonal decomposition graph of time series for theft offence

The above fig 3.3 chart of decomposition shows the description of the data on theft after differencing once which shows that the movement of the trend is not really affected by time thereby normalizing the data to be stationary. Also, it shows the seasonality of the data which reveal that there is presence of seasonal component in the series and therefore seasonal ARIMA MODEL becomes appropriate in order to correct or adjust for seasonality.

Table 3.4 TEST FOR AUTOCORRELATION AND PARTIAL AUTOCORRELATION

Lag	ACF	PACF
1	-0.29	-0.29
2	-0.13	-0.23
3	0.01	-0.12
4	-0.19	-0.3
5	0.17	-0.03
6	-0.02	-0.08
7	0.02	-0.01
8	0.13	0.13
9	-0.06	0.11
10	-0.2	-0.17
11	0.11	0.01
12	0.09	0.11
13	0.1	0.19
14	-0.04	0.06
15	-0.26	-0.18
16	0.12	-0.04
17	-0.04	-0.09
18	-0.03	-0.13
19	0.13	-0.06
20	0.07	0.09
21	-0.12	-0.08

For the correlograms analysis, a maximum lag of 21 was used with their respective ACF's and PACF's. The corresponding ACF and PACF's values are provided in Table 3.4

CORRELOGRAM GRAPH FOR THEFT

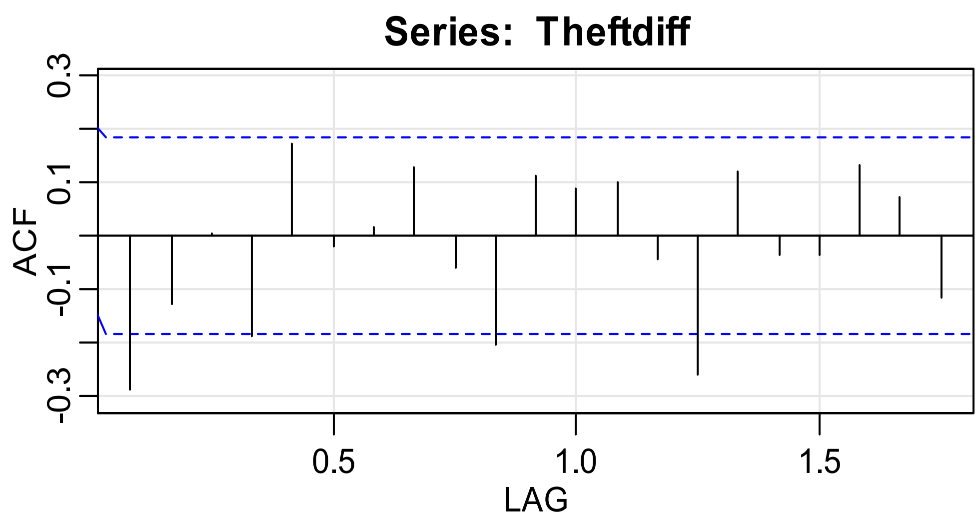

Fig 3.4a showing the ACF chart for Theft Offence

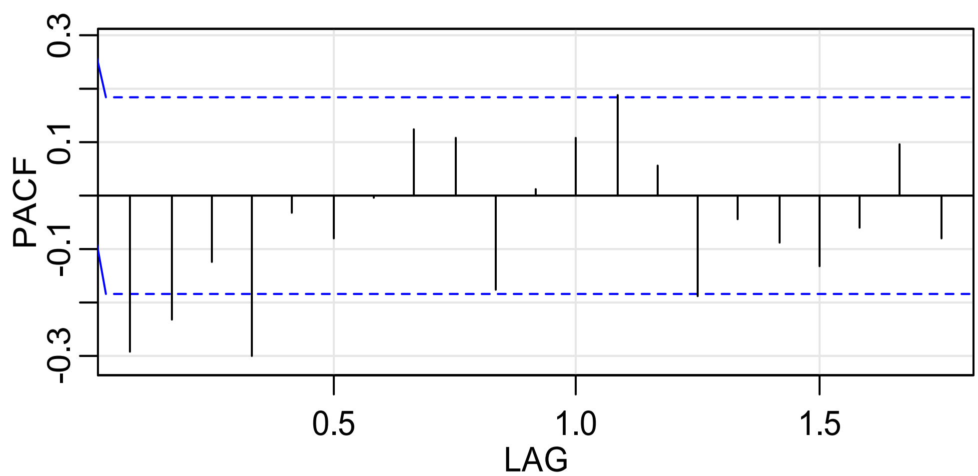

Fig 3.4b showing the PACF chart for Theft

Interpretation: Fig 3.4a chart of ACF for Theft shows lag 1 to be significant negatively (-0.29), lag 59 with a small cut off from the boundary to be negatively significant (-0.06) and lag 14 is also negatively significant (-0.04). Likewise, fig 3.4b of the PACF shows lag 1, lag 2 and lag 4 to be significant negatively (-0.29,-0.23 and -0.3); therefore since the ACF is significant at the first lag and the PACF is significant at the first and the second lag; parsimoniously, we suggest the model SARIMA(1,1,2)(1,1,0)12 with one seasonal difference for the original time series.

Table 3.5: Showing the Parsimoniously Selected Models with their respective AIC value

Selection of Model

MODE	MODEL TYPE	AIC Value
1	SARIMA(2,1,2)(2,0,0)[12]	901.87
2	SARIMA(0,1,1)(2,0,0)[12]	898.98
3	SARIMA(1,1,2)(2,0,0)[12]	899.16
4	SARIMA(2,1,1)(1,0,0)[12]	900.49
5	SARIMA(1,1,0)(2,0,0)[12]	911.72

Note that, having selected all these models with their respective AIC in the above table 3.5, and also using auto.arima command, it is shown that the best model is the model with the least AIC Value which is SARIMA (0,1,1)(2,0,0)[12] having its AIC Value to be 898.98.

Table 3.6 Best model: SARIMA(0,1,1)(2,0,0)[12] with zero mean

Series: Theft

SARIMA(0,1,1)(2,0,0)[12] with zero mean

Coefficients:			
	ma1	sar1	sar2
	-0.5905	0.2249	-0.0382
s.e.	0.0860	0.1039	0.1214

sigma^2 estimated as 106.3: log likelihood=-445.49

AIC=898.98 AICc=899.33 BIC=910.1

$$\mathbf{Y_t = -0.5905e_{t-1} - 0.2249_{t-12} + 0.0382_{t-12}}$$

Table 3.7 SHOWING PREDICTIONS FOR JANUARY to DECEMBER, 2016

Point	Forecast	Lo.95	Hi.95
Jan-16	9.591449	-10.6149	29.7978
Feb-16	9.816333	-12.0188	31.65147
Mar-16	10.90256	-12.448	34.25315
Apr-16	11.61113	-13.1624	36.38463
May-16	10.5249	-15.5941	36.64392
Jun-16	11.98879	-15.4098	39.38732
Jul-16	11.20383	-17.4171	39.82474
Aug-16	11.43299	-18.3602	41.22616
Sep-16	11.8021	-19.1189	42.72312
Oct-16	11.53902	-20.4701	43.54818
Nov-16	10.94075	-22.1208	44.00226
Dec-16	9.472596	-24.6088	43.55397

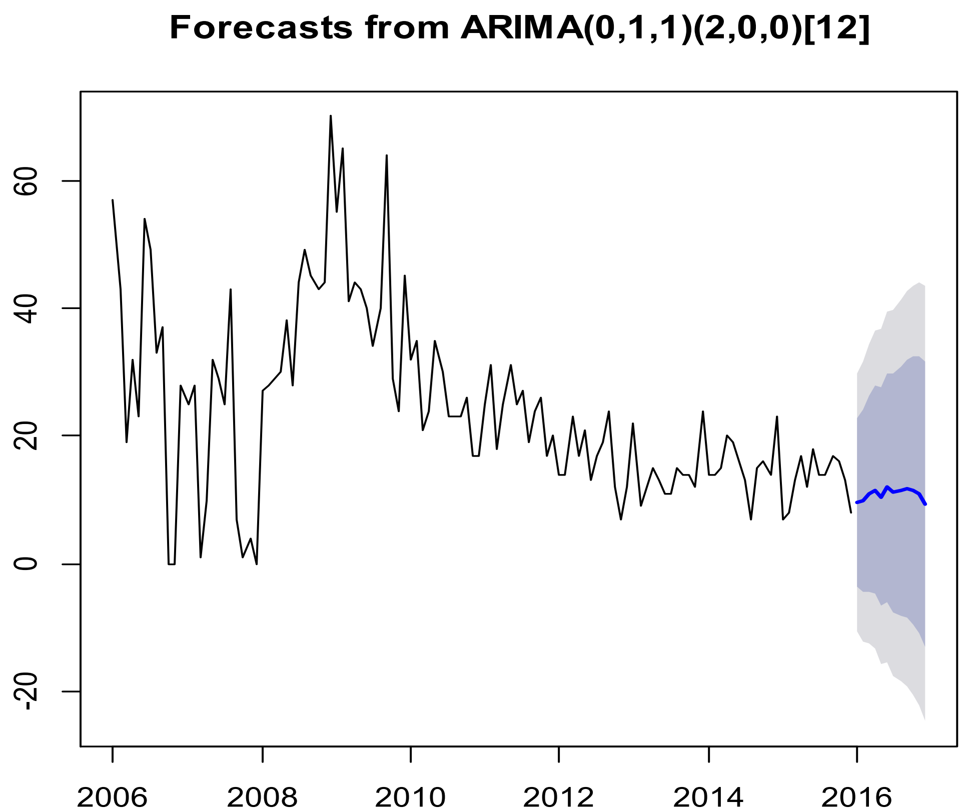

Fig 3.5 showing the forecast graph from the ARIMA(0,1,1)(2,0,0)[12] model

The chart in fig 3.5 above shows the forecast for Theft criminal offence for the year 2016 with the upper and lower limits of 95% and 80% respectively

DIAGONISTIC TEST FOR THE MODEL

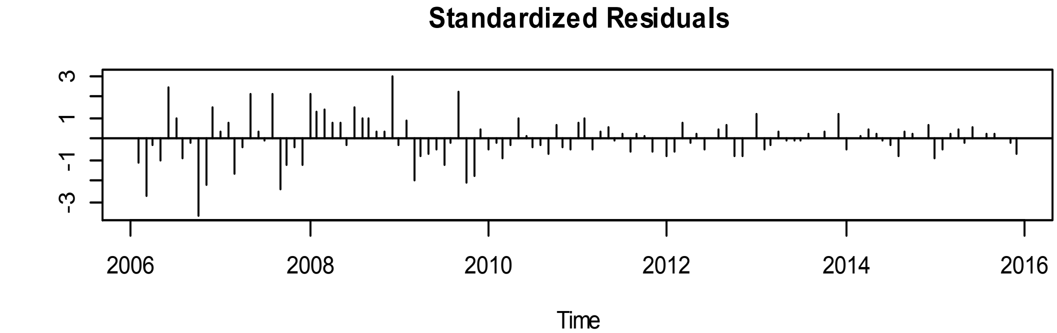

Fig 3.6a: Diagnostic Test (Standardized Residual)

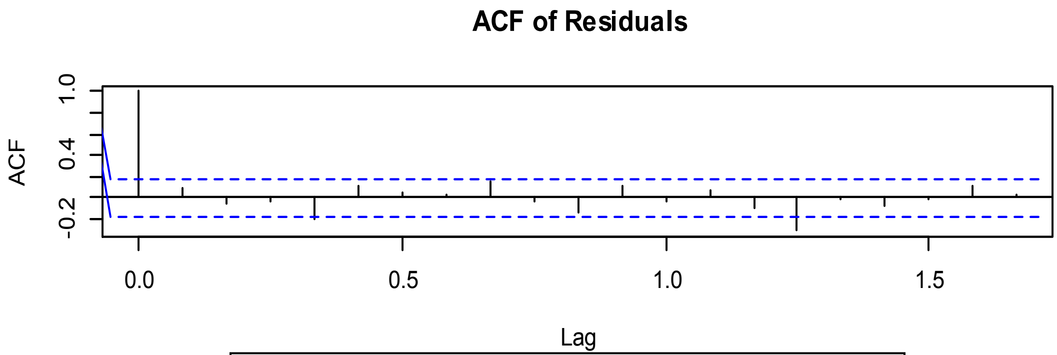

Fig 3.6b: Diagnostic Test (ACF of Residual)

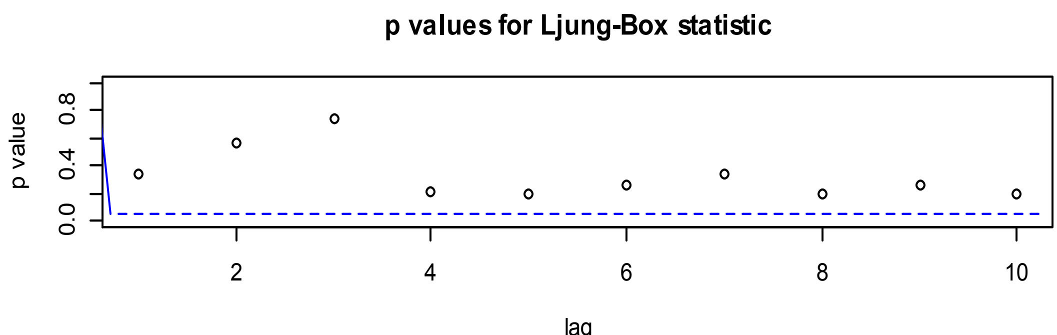

Fig 3.6c: Diagnostic Test (p-value for Ljung-Box statistic)

Fig 3.6a, 3.6b and 3.6c above shows that the model is independently distributed residuals, that is, the residual shows that the model is random. Also the ACF of Residual showed that nearly all the spikes are within the line of boundary and the Ljung-Box statistics showed that all p-value points are above 0.05 thereby showing the accuracy of the model is good to forecast.

Table 3.8 BOX-LJUNG TEST FOR FORECAST ERROR

Box-Ljung test
data: b$residual
X-squared = 29.099, df = 20, p-value = 0.08584

The appropriate hypotheses for conducting Box-Ljung Tests are as follows:

Null hypothesis, H_0: No residual autocorrelation

Versus

Alternative hypothesis, H_1: Presence of residual autocorrelation

By adopting the conventional Decision Rule, the decision arising from the entries in Table 3.8 is not to reject Ho, since p-value (=0.08584) is greater than level of significance, α (=0.05);

Hence, the appropriate conclusion is that there is no residual autocorrelation i.e. there is evidence of non-zero autocorrelations in the forecast errors at lags 1 to 21.

TESTING FOR THE NORMALITY OF THE FORECAST RESIDUAL

The test for the normality of the forecast errors is done by plotting the time plot for the forecast errors and check whether they meet the assumption of normality.

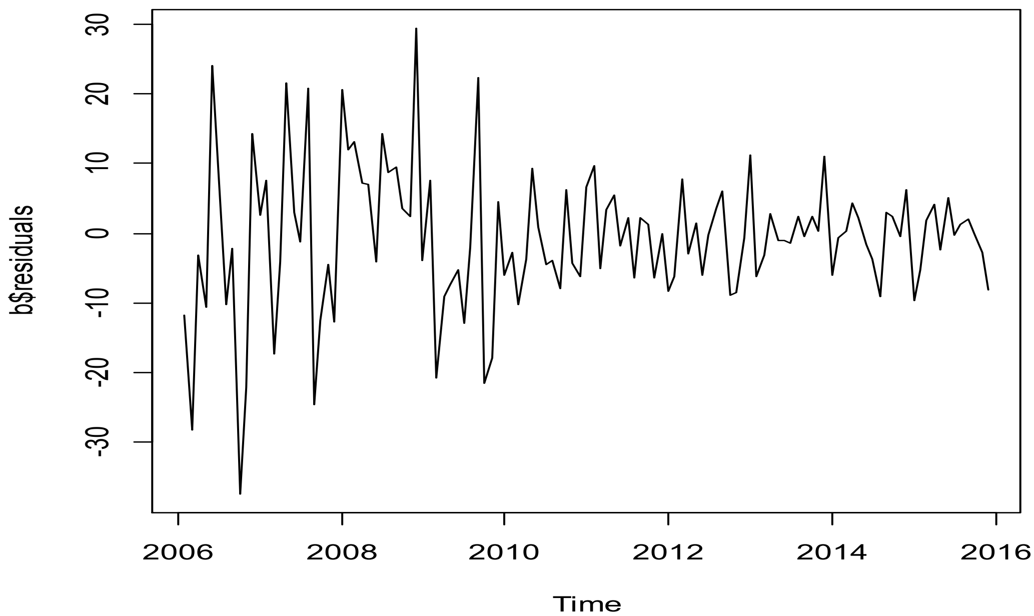

Fig 3.7 showing the plot for forecast error to check if assumption of normality is satisfied

The time plot of the in-sample forecast errors in fig 3.7 shows that the variance of the forecast errors seems to be roughly constant over time (though perhaps there is slightly higher variance for the first half of the time series). Therefore, it is plausible that the forecast errors are normally distributed with mean zero and constant variance. Since successive forecast errors do not seem to be correlated, and the forecast errors seem to be normally distributed with mean zero and constant variance, the SARIMA(0,1,1)(2,0,0)12 does seem to provide an adequate predictive model for the monthly record of Theft criminal offence in Kwara State.

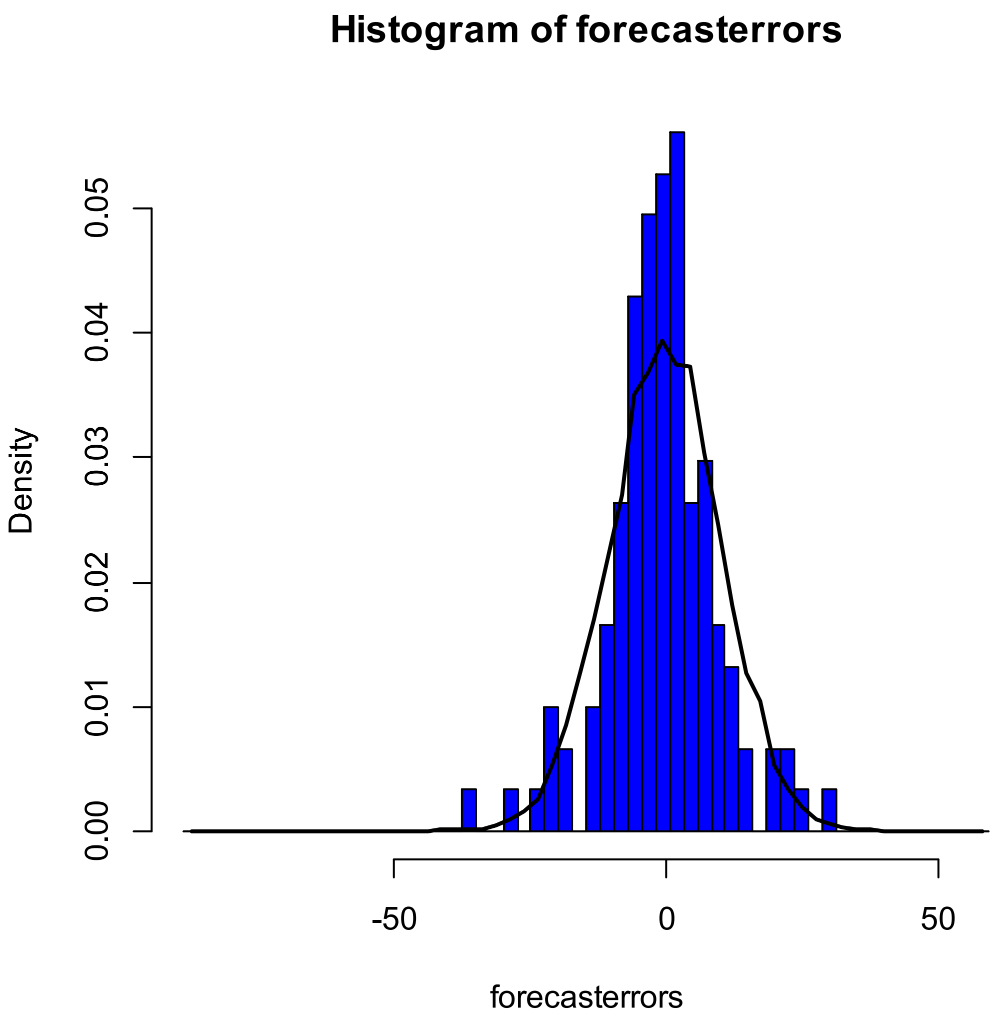

Fig 3.8: Histogram of forecast errors

The histogram in fig 3.8 above shows the residual for the forecast which reveal that the error term for the forecast satisfy the assumption of normality, i.e. residual of the forecast is normally distributed.

3.2 PRESENTATION OF DATA ON ASSAULT CRIMINAL OFFENCE

Table 3.9 showing monthly data on Assault Offence in Kwara State from 2006 to 2015

YEAR/ MNTHS	JAN	FEB	MAR CH	APRIL	MAY	JUNE	JULY	AUG	SEPT	OCT	NOV	DEC
2006	39	23	23	32	17	10	16	3	23	16	9	6
2007	17	14	14	12	10	8	11	1	9	15	0	7
2008	3	6	0	8	3	3	14	20	10	0	3	0
2009	14	26	22	13	12	17	14	13	12	7	11	15
2010	12	13	7	7	8	4	8	10	8	10	5	2
2011	10	9	8	6	8	9	5	9	4	8	4	2
2012	3	4	2	5	6	4	3	2	2	0	0	6
2013	0	1	1	4	1	1	1	3	1	6	3	4
2014	4	1	6	4	5	5	5	3	5	4	6	8
2015	2	1	5	4	3	5	4	1	3	2	10	0

SOURCE: kwara State Police Command Headquarter

Table 3.9 above shows the recorded number of Assault offence in Kwara State from which the highest value was recorded in the month of January 2006. 2013 has the smallest record on assault offence in the state while 2006 has the highest record.

TIME PLOT FOR ASSAULT OFFENCE DATA

The below fig 3.9 shows that the pattern of movement of Assault criminal offence which ranges from 2006 through 2015; it shows reduction in recorded Assault offence from year 2010

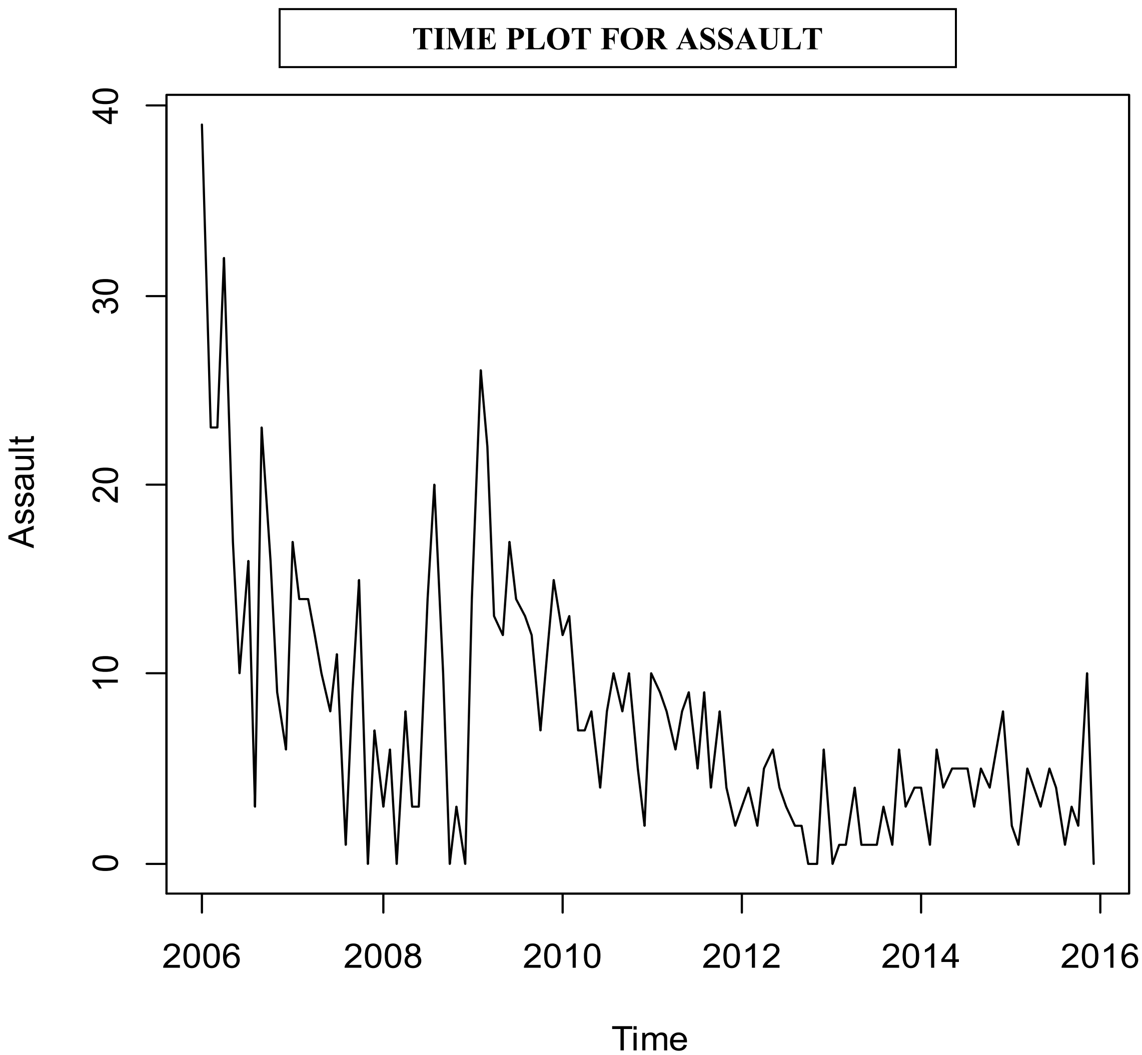

Fig 3.9: Time Plot for Assault Offence

SEASONAL DECOMPOSITION GRAPH OF TIME SERIES FOR ASSAULT OFFENCE

To estimate the trend, seasonal and irregular components of the time series, the monthly number of Assault criminal offence is decomposed into the various component by using the function decompose() in R. By decomposing the time series, we obtain;

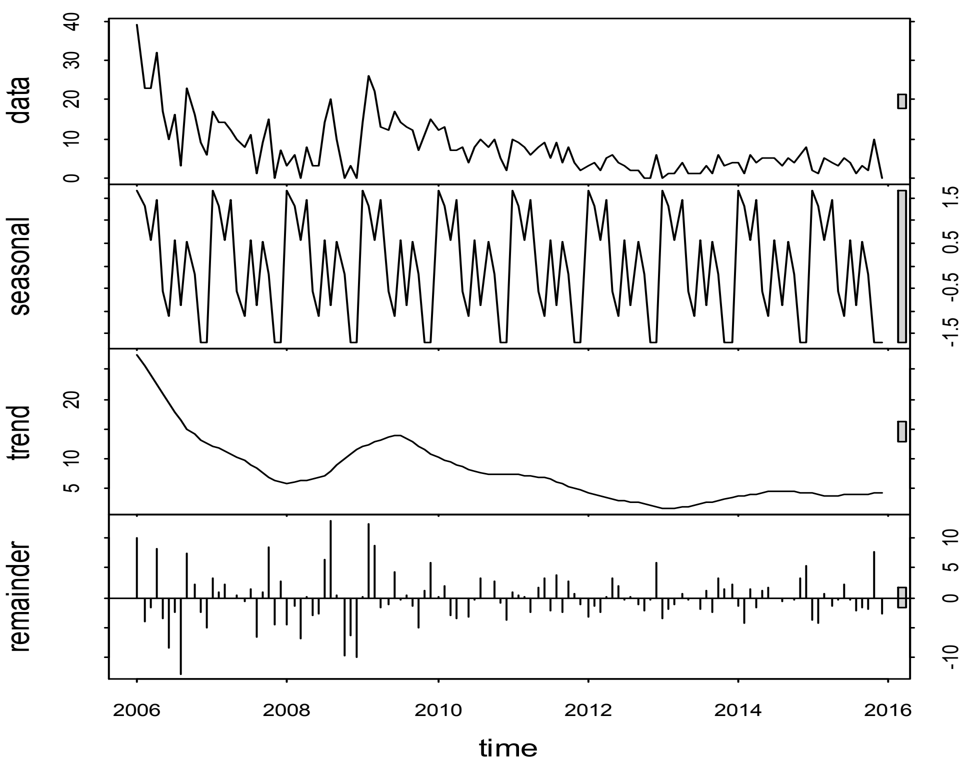

Fig 3.10 shows the seasonal decomposition graph of Time Series for Assault Offence

The above chart in fig 3.10 shows the description of the data which shows that the movement of the trend is not really affected by time thereby normalizing the data to a constant mean and a constant variance. Also, it shows the seasonality of the data which reveal that there is presence of seasonal component in the series and therefore seasonal ARIMA MODEL becomes appropriate in order to correct or adjust for seasonality.

UNIT ROOT TEST OF STATIONARY

Table 3.10 DICKEY-FULLER TEST FOR ASSAULT OFFENCE

Augmented Dickey-Fuller Test
data: Assault
Dickey-Fuller = -4.4411, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary
Warning message:
In adf.test(Assault) : p-value smaller than printed p-value

The appropriate hypotheses for conducting Dickey-Fuller Tests are as follows:

Null hypothesis, H_0: There is no stationary

Versus

Alternative hypothesis, H_1: There is stationary

By adopting the conventional Decision Rule, the decision arising from the entries in Table 3.10 is since p-value (0.01) is less than the significant level, $\alpha(= 0.05)$;

Hence the appropriate conclusion is the dataset is stationary at 0.05 level of significant. The consequence of this conclusion is that the condition of stationarity has been affirmed, and therefore there is no need to perform any form of differencing.

Table 3.11 TEST FOR AUTOCORRELATION AND PARTIAL AUTOCORRELATION FOR ASSAULT OFFENCE

Lag	ACF	PACF
1	0.57	0.57
2	0.45	0.18
3	0.41	0.16
4	0.31	-0.01
5	0.33	0.13
6	0.4	0.2
7	0.3	-0.06
8	0.3	0.05
9	0.27	0
10	0.24	0.04
11	0.21	-0.04
12	0.21	0.01
13	0.16	-0.03
14	0.08	-0.12
15	0.11	0.05
16	0.09	-0.02
17	0.12	0.08
18	0.12	-0.01
19	0.04	-0.09
20	0.05	0.04
21	0.04	-0.03

For the correlograms analysis, a maximum lag of 21 was used with their respective ACF's and PACF's. The corresponding ACF and PACF's values are provided in Table 3.11

CORRELOGRAM GRAPH FOR ASSAULT OFFENCE

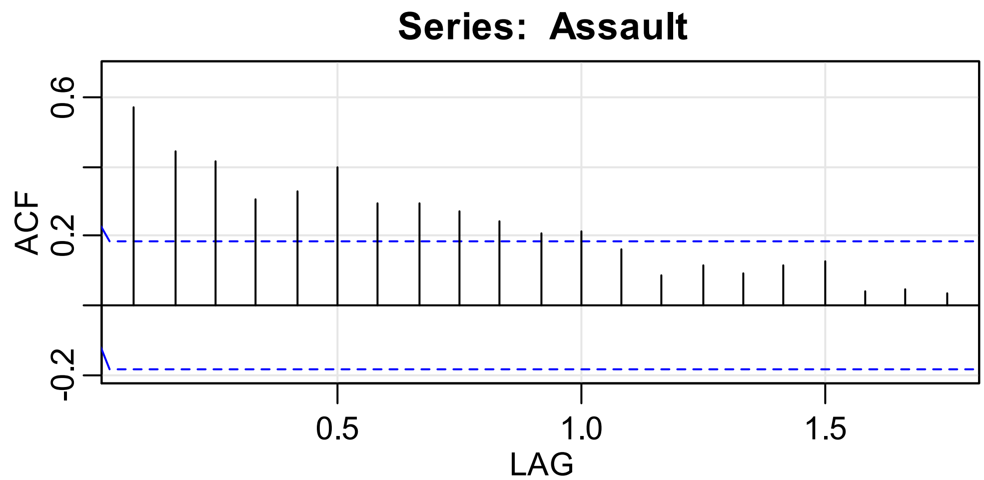

Fig 3.11a: Showing the ACF chart for Assault Offence

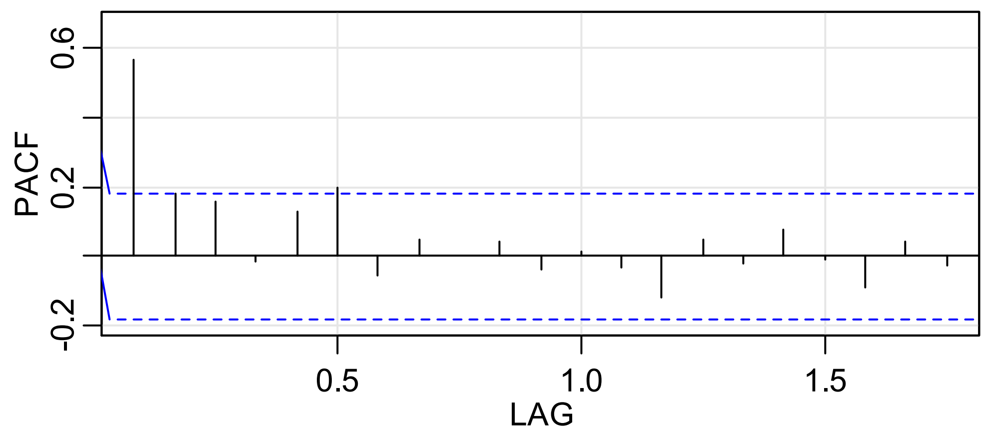

Fig 3.11b: Showing the PACF chart for Assault Offence

Interpretation: Fig 3.11a chart of ACF for Assault shows lag 1 to lag 12 appear to differ significantly from zero (they lay outside the 95% confidence bound), and they are positive. This indicates that some months has an above average criminal offence on assault; given MA(0). Likewise, fig 3.11b for the PACF shows lag 1 to be significant positively thereby showing an AR(1). Parsimoniously, showing ARIMA(1,0,0).

Table 3.12: Showing the Parsimoniously Selected Models with their respective AIC value

Selection of Model

MODE	MODEL TYPE	AIC Value
1	**SARIMA(1,1,2)(1,0,1)[12]**	**730.65**
2	**SARIMA(1,1,2)(2,0,0)[12]**	**730.56**
3	**SARIMA(0,1,2)(2,0,1)[12]**	**730.75**
4	**SARIMA(1,1,2)(1,0,0)[12]**	**728.67**
5	**SARIMA(0,1,2)(2,0,0)[12]**	**728.93**

Note that, having selected all these models with their respective AIC, and also using auto.arima command, it is shown that the suitable model is the model with the least AIC Value which is SARIMA(1,1,2)(1,0,0)[12] having its AIC Value to be 728.67

Table 3.13 **MODEL PARAMETER**

```
Call:

arima(x = Assault, order = c(1, 1, 2), seasonal = c(1, 0, 0))

Coefficients:

         ar1      ma1      ma2    sar1
     -0.2826  -0.2469  -0.3310  0.0207
s.e.  0.4031   0.3837   0.2379  0.1135

sigma^2 estimated as 24.45:  log likelihood = -359.33,  aic = 728.67
```

$$\mathbf{Y_t = -0.2469e_{t-1} - 0.3310e_{t-2} + 0.2826_{t-1} - 0.0207_{t-12} + 0.0058_{t-13}}$$

Table 3.14 Showing Predictions of Assault Offence for January to December, 2016

Point	Forecast	Lo.95	Hi.95
Jan-16	1.822345	-7.86941	11.5141
Feb-16	3.364583	-7.34637	14.07554
Mar-16	3.005776	-8.06576	14.07731
Apr-16	3.109879	-8.44278	14.66254
May-16	3.053879	-8.92287	15.03063
Jun-16	3.105295	-9.29121	15.5018
Jul-16	3.081754	-9.71795	15.88146
Aug-16	3.020381	-10.171	16.21174
Sep-16	3.061602	-10.5099	16.6331
Oct-16	3.040942	-10.9004	16.98228
Nov-16	3.206711	-11.0949	17.5083
Dec-16	2.999483	-11.6535	17.65249

The chart in fig 3.12 below shows the forecast for Assault criminal offence for the year 2016 with the upper and lower limits of 95% and 80% respectively.

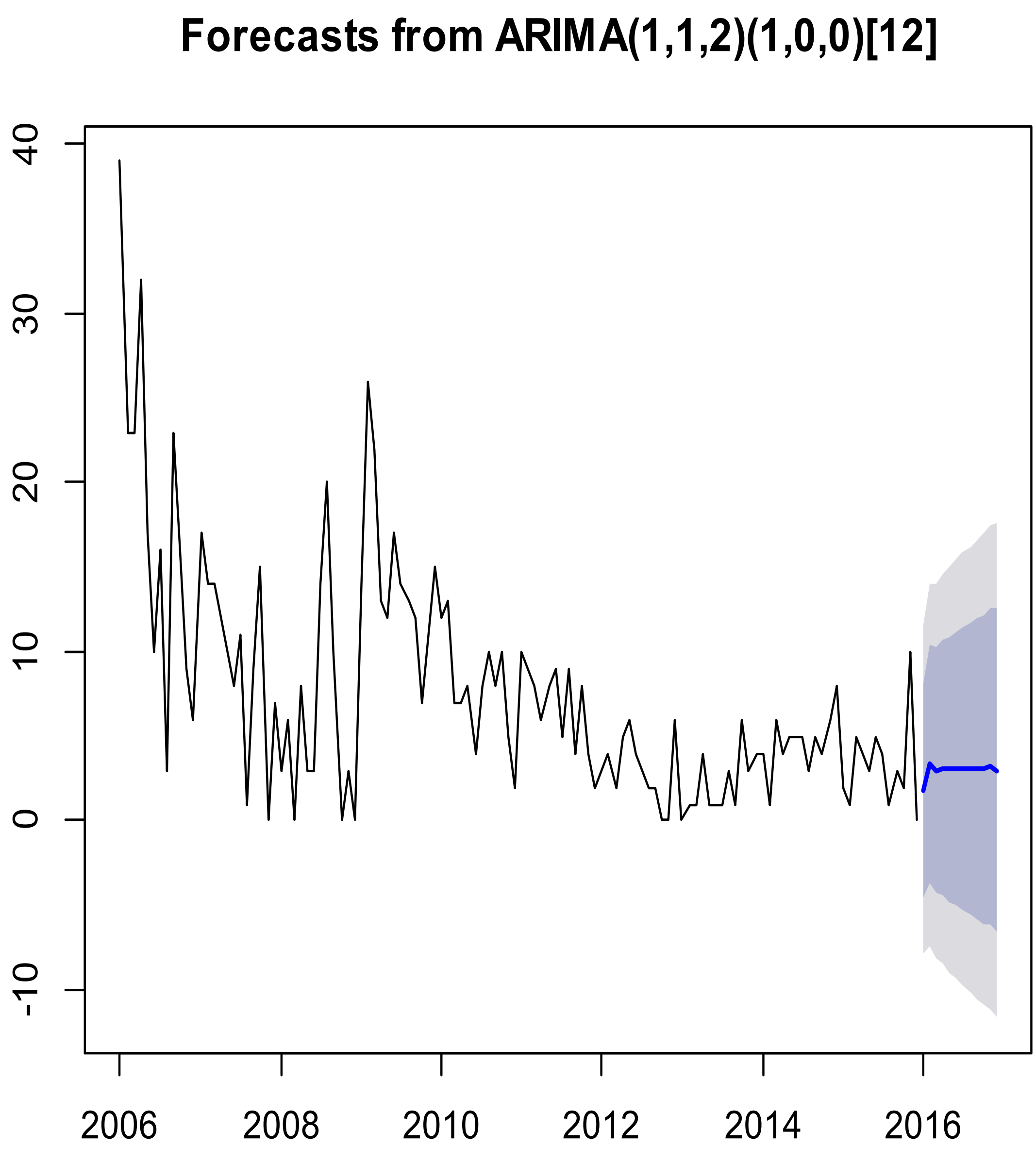

Fig 3.12 Showing the forecast graph from ARIMA(1,1,2)(1,0,0)[12]

<u>**DIAGONISTIC TEST FOR ASSAULT MODEL**</u>

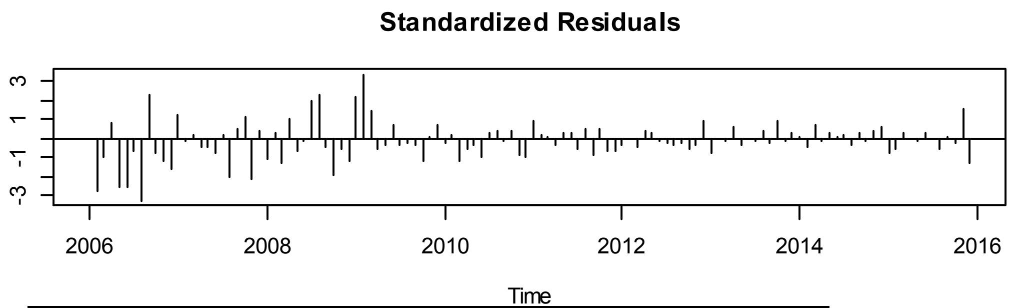

Fig 3.13a: Diagnostic Test (Standardized Residual)

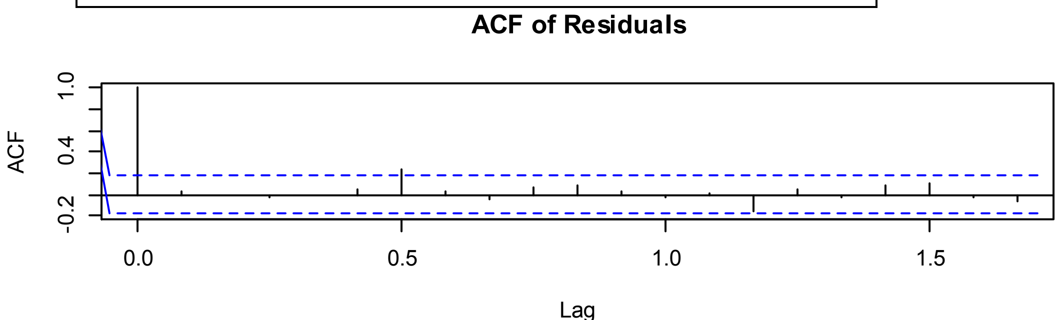

Fig 3.13b: Diagnostic Test (ACF of Residual)

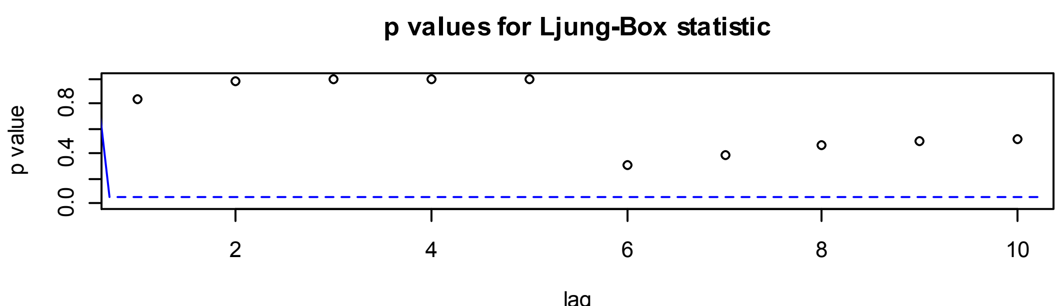

Fig 3.13c: Diagnostic Test (p-value for Ljung-Box statistic)

Figs 3.13a, 3.13b and 3.13c shows that the model is independently distributed residuals, that is, the residual shows that the model is random. Also the ACF of Residual shows that nearly all the spikes are within the line of boundary and the Ljung-Box statistics shows that all p-value points are above 0.05 thereby showing the accuracy of the model is good to forecast.

Table 3.15 BOX-LJUNG TEST FOR FORECAST ERROR

Box-Ljung test
data: t$residual
X-squared = 14.663, df = 20, p-value = 0.7953

The appropriate hypotheses for conducting Box-Ljung Tests are as follows:

Null hypothesis, H_0: No residual autocorrelation

Versus

Alternative hypothesis, H_1: Presence of residual autocorrelation

By adopting the conventional Decision Rule, the decision arising from the entries in Table 3.15 is not to reject Ho, since p-value (=0.7953) is greater than level of significance, α (=0.05).

Hence, the appropriate conclusion is that there is no residual autocorrelation i.e. there is evidence of non-zero autocorrelations in the forecast errors at lags 1 to 21.

TESTING FOR THE NORMALITY OF THE FORECAST

The test for the normality of the forecast errors is done by plotting the time plot for the forecast errors and check whether they meet the assumption of normality.

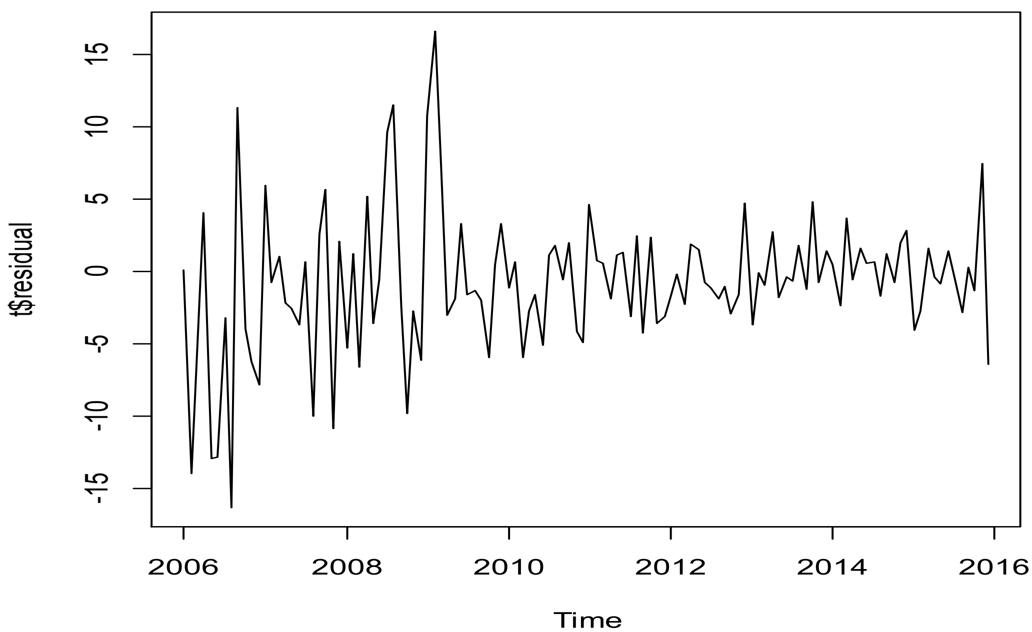

Fig 3.14: Showing the plot for forecast error to check if assumption of normality is satisfied

The time plot of the in-sample forecast errors in fig 3.14 shows that the variance of the forecast errors seems to be roughly constant over time (though perhaps there is slightly higher variance for the first half of the time series). Therefore, it is plausible that the forecast errors are normally distributed with mean zero and constant variance. Since successive forecast errors do not seem to be correlated, and the forecast errors seem to be normally distributed with mean zero and constant variance, the SARIMA(1,1,2)(1,0,0)12 does seem to provide an adequate predictive model for the monthly record of Assault criminal offence in Kwara State.

3.3 DISCUSSION OF RESULTS

The summary of this study is that after plotting the time plots against time (t), Theft exhibited a non-stationarity of which we differenced so as to make it stationary which was achieved after the first differencing; likewise Assault exhibited a constant mean and variance, also the test for the seasonality showed there was seasonality present in the data's' (Theft and Assault).

Also, the test for the stationarity showed that the data for Theft was not stationary and after differenced, it was stationary. The test for stationary showed the data for Assault to be stationary. The ACF table for Theft shows lag 1 to be significant negatively (-0.29), lag 9 with a small cut off from the boundary to be negatively significant (-0.06) and lag 14 also shows negatively significant (-0.04). Likewise, the PACF shows lag 1, lag 2 and lag 4 to be significant negatively (-0.29,-0.23 and -0.3); therefore since the ACF is significant at the first lag and the PACF is significant at the first and the second lag, thus this suggested the model SARIMA(1,1,2)(1,1,0)12 with one seasonal difference for the original time series. The ACF table for Assault shows lag 1 to lag 12 appear to differ significantly from zero (they lay outside the 95% confidence bound), and they are positive. This indicates that some months has an above average criminal offence on assault; given MA (0). Likewise, the PACF shows lag 1 to be significant positively thereby showing an AR (1); parsimoniously, suggested an ARMA (1,0,0). Then a test for the adequacy of the fitted model was carried out using the Ljung-Box test which confirms the adequacy of the model. A forecast for 12months was carried out.

The model developed was also used in forecasting for 12months starting from January 2016-December 2016, 95% confidence interval forecast and the time plot of the forecasted data depicts a parallel movement with time.

CHAPTER FOUR

4.0 SUMMARY, CONCLUSION AND RECOMMENDATIONS

4.1 SUMMARY

The summary of this study is that after plotting the time plots against time (t), Theft exhibited a non stationary data of which we differenced once so as to make it stationary; also the test for the seasonality showed there was seasonality present in the data's' (Theft).

Also, the test for the stationarity showed that the data for Theft was not stationary and after the first differenced, it was stationary. The ACF table for the data showed lags 1, 9 and 14 to be significant negatively (-0.29,-0.06,-0.04) respectively. Likewise, the PACF shows lag 1, lag 2 and lag 4 to be significant negatively (-0.29,-0.23 and -0.3). A best model was selected which is SARIMA(0,0,1)(2,0,0)[12] ; then a test for the adequacy of the fitted model was carried out using the Ljung-Box test which confirms the adequacy of the model. A forecast for 12months was carried out.

The model developed was also used in forecasting for 12months starting from January 2016-December 2016, 95% confidence interval forecast and the time plot of the forecasted data depicts a nearly constant movement with time.

4.2 CONCLUSION

Based on the analysis carried out, Kwara State may likely experience decrease in crime rates after which the occurrence will continue to follow the historic pattern. In essence, Kwara state is moderately save but a critical examination of the forecast ignites fear of victimization if government and security stakeholders do not intensify efforts and map out strategies of bringing the prediction under control.

4.3 RECOMMENDATIONS

The SARIMA models are recommended for forecasting Crime rate in Kwara state whilst but the following precaution measures should be taken into consideration in order to prevent wrong application of model which in turn may lead to spurious and misleading forecasting values into the future:

i. The models should not be used to forecast long time ahead (preferably a maximum of 12months). This is because long time periods could lead to arbitrary large forecasts values.
ii. Any researcher who wishes to embark on this type of sensitive programme in future should endeavor to include households or individuals as a complementing sources of obtaining information as majority of serious crimes to people often a times do not reach police stations.
iii. The efforts of Kwara State government Police authority to rid criminals of all shades out of the state although not parts of this programme but has been tremendously curbing the menace but there seemed to be a long way to go.
iv. Government is therefore advised to aside Security operatives engage Landlords, Household heads, market women, communities/street leaders and elders as an extended mediums of getting security information.

v. Most of the police stations which charges people who reported crime issues to them also have made reporting of crimes issues by low income earners and day laborers almost an impossible tasks.

vi. Periodic incentives and encouragement should be given to Police officers who endangered their lives for the security of the community.

vii. Above all, periodic orientation and sensitization programs should be carried out to inform people of relevance of security and the need to not taken suspicious issues or people around their niche and vicinities with levity hands.

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