CHAPTER 1

INTRODUCTION

1.1 Background to the study

In Ghana hardly does the day go by without government officials, politicians and economist talking about inflation. In some cases we are told inflation is high for a particular month and low for another month. There are several important variables that help to describe the state of an economy. These include inflation, unemployment, the budget balance, the interest rate, and the balance of payments. Inflation may be defined as a rise in the average level of a group of prices in a country. The term is sometimes restricted to prolonged or sustained rises. Inflation creates a problem because the purchasing power of money falls as the price level rises. It imposes an opportunity cost on holders of money. Thus inflation will reduce the real value of money wage, and savings accounts making holders of these instruments to lose. Inflation also encourages wasteful increase in the volume and frequency of transactions people undertake and because it is difficult to foresee, it adds to the uncertainties of economic life. In real terms, inflation means your money cannot buy as much as what it could have bought yesterday. Inflation retards economic growth because the economy needs a certain level of savings to finance investments which boosts economic growth. Inflation causes global concerns because it can distort economic patterns and can result in the redistribution of wealth when not anticipated. Inflation can also discourage investors within and without the country by reducing their confidence level in investments. This is because investors expect high possibility of returns so that they can make good financial decisions. There are two main types of inflation. These are

- Creeping or moderate inflation and
- Hyper inflation.

The creeping inflation, also known as mild inflation, is the type in which the rate of price change is not so severe. Example of creeping inflation is the one Ghana experienced in 1992, 1999, 2002; 2004-2007 and 2010 A rate of inflation of about 10% annually can be described as creeping inflation. The hyper inflation is the type in which the rates of change in prices are so severe. A typical example of hyper inflation is what has happened in Zimbabwe from 2007 to 2008. This country had a rate of inflation of about 8000%.This means that if you buy an item today in the morning, the price of the item will change by the time you go there in the evening. The hyper inflation is the worse economic problem any country will experience. The effect of inflation is highly considered as a crucial issue for a country. The inflation problems make a lot of people living in a country much harder. People who are living on fixed income suffer most as when prices of commodities rise, since these people cannot buy as much as they could previously.

1.2 Statement to the problem

In this study, the problem is to forecast Ghana’s monthly inflation rate using time series Seasonal Autoregressive Integrated Moving Average (SARIMA) models. When it comes to forecasting, there are extensive number of methods and approaches available and their relative success or failure to outperform each other is in general conditional to the problem at hand. The rational for choosing this type of model is contingent on the behaviour of the time series data. Also in the history of inflation forecasting, this model has proved to perform better than other models.

1.3 Research goal

The goal of this research is to forecast inflation rates in Ghana using SARIMA models with the best forecasting techniques resulting in the minimum performance error. The enhancement and precision in this forecast will assist the central bank (Bank of Ghana) to develop an effective monetary policy for the country and also predict future macroeconomic developments of the country

1.4 Objectives of the Study

The objectives of this study are

(i) to analyze the trends of inflation rates in Ghana from 1990 to 2010.

(ii) to model and forecast twelve (12) months inflation rates of Ghana outside the sample periods.

The post–sample forecasting is very important for economic policy makers to foresee ahead of time the possible future plans to design economic strategies and effective monetary policies to combat any expected high inflation rates in Ghana. Forecast will also play a crucial role in business, industry, government, and institutional planning because many important decisions depend on the anticipated future values of inflation rates. We also believe that this research will serve as a literature for other researchers.

1.5 Methodology

The methodology propounded by Box-Jenkins called Autoregressive Integrated Moving Average (ARIMA) models are used. This is an advance forecasting technique that takes into account historical data and decomposes it into an Autoregressive (AR) process, where there is a memory of past values; an Integrated (I) process, which accounts for stabilizing or making the data stationary plus a

Moving-Average (MA) process, which accounts for previous error terms making it easier to forecast. In the forecasting process, data on inflation in Ghana are collected from the past years.

1.5 1 Data

Data for this study are the monthly inflation rate figures from 1990- 2010 of Ghana. These data were collected from the Ghana Statistical Service and the Bank of Ghana. These were fed into the Autoregressive Moving Average (ARIMA) model and analyzed. This involved testing the model with the historic data and the outcome examined. The data are considered as a univariate time series. The data collected for the period are under the assumption that the days of the months in a year are equal.

1.5.2 Software and data processing

MINITAB statistical software was used to construct the ARIMA model based on the monthly inflation figures of Ghana, from January 1990- to December 2010. The model were trained using data for the period January 1990 to December 2009. Akaike's information criterion (AIC) and Bayesian information criterion (BIC) were used to confirm the fitness of model. The constructed model was validated using the remaining data for the period January 2010 to December 2010. The constructed model was then applied to predict the monthly inflation rate from January 2011 to December 2011.

1.5.3 Scope and Limitations

In order to make a fair and comprehensive analysis and forecast, we set out to analyse twenty (20) years of monthly inflation rate of Ghana that is analysing 240 data points. The forecasting time horizon for this research is short-range because most ARIMA models have short term memories and tend to be more accurate than longer-range forecast. Also some of the traditional model identification techniques are subjective and the reliability of the chosen model can depend on the skill and experience of the forecaster (although this criticism often applies to other modelling approaches as well). Furthermore, the economic significance of the chosen model is not clear therefore it is not possible to run policy simulations with the model.

1.6 Justification

Inflation is a macroeconomic variable and it is a challenge facing most countries in Africa with Ghana not being exception. Inflation is a major focus of economic policy worldwide as described by David (2001). Meanwhile there has been very little research work done on Ghana's inflation. These reasons have given us the impetus to research into Ghana's inflation.

1.7 Organisation of the study

Chapter 1 presents the background, problem statement, objective of the study, methodology, scope and limitation as well as justification of this study. In Chapter 2 we shall review some pertinent literature on inflation and that required for the work carried out in remaining three chapters. In addition to that literature on areas of application of classical time series models and ARIMA models are included. In chapter 3 the processes involved in the building of the model were developed. It contains the well known Box-Jenkins ARIMA modelling technique - model identification, diagnostic checking, and model selection. In Chapter 4 the results are discussed and analysed and the best forecasting model selected. Finally summary of the results obtained in Chapter 4, discussion of results, recommendation and conclusion to the study are in Chapter 5

CHAPTER 2

LITERATURE REVIEW

2.1 Mathematical Models and Forecasting

A model is a description of a physical system that may be used to predict or explain the behaviour of the system. It is an external and explicit representation of a part of reality, as seen by individuals who wish to use this model to understand change and control that part of reality.

Forecasting is the art and science of predicting future events. It may involve taking historical data and projecting them into the future with some sort of mathematical model.

A mathematical model is the use of mathematical language to describe the behaviour of a system, be it biological, economic, electrical, mechanical, thermodynamic, or one of many other examples. For instance if an engineer analyses a system or is supposed to control a system, he uses a mathematical model. In analysis, the engineer can build a descriptive model of the system as a hypothesis of how the system could work, or try to estimate how an unforeseeable event could affect the system. Similarly, in control of a system the engineer can try out different control approaches in simulations.

A mathematical model usually describes a system by means of variables. The values of the variables can be practically anything; real or integer numbers, Boolean values or strings, for example. The variables represent some properties of the system, for example, measured system outputs often in the form of signals, timing data, counters, event occurrence (yes/no). The actual model is the set of functions that describe the relations between the different variables.

Mathematical models can be divided up several ways, they can be deterministic (that is perform the same way for a given set of initial conditions), or stochastic (randomness is present, even when given an identical set of initial conditions). They can also be continuous or discrete.

2.2 Model evaluation

An important part of the modelling process is the evaluation of an acquired model. How do we know if a mathematical model describes the system well? This is not an easy question to answer. Usually the engineer has a set of measurements from the system which are used in creating the model. Then, if the model was built well, the model will adequately show the relations between system variables for the measurements at hand. The question then becomes: How do we know that the measurement data is a representative set of possible values? Does the model describe well the properties of the system between the measurement data (interpolation)? Does the model describe well events outside the measurement data (extrapolation)? A common approach is to split the measured data into two parts; training data and verification data. The training data is used to train the model, that is, to estimate the model parameters. The verification data is used to evaluate model performance. Assuming that the training data and verification data are not the same, we can assume that if the model describes the verification data well, then the model describes the real system well. However, this still leaves the extrapolation question open. How well does this model describe events outside the measured data? Consider for example Newtonian classical mechanics-model. Newton made his measurements without advanced equipment, so he could not measure properties of particles travelling at speeds close to the speed of light. Likewise, he did not measure the movements of molecules and other small particles, but macro particles only. It is then not surprising that his model does not extrapolate well into these domains, even though his model is quite sufficient for ordinary life physics there are several forecasting methods and there is seldom one single superior method. What works best in an organization under one set of conditions may be a complete disaster in another organization, or even in a different department of the same organization. In addition there are limits as to what can be expected from forecasts, and they are not perfect.

Information about future events from forecasts are usually a critical input into a wide range of managerial and administrative decision-making, since today's plans are dependent on future expectations. Forecasts are numerical estimates of future levels of sales, demand, inventories, costs, imports, exports, and prices, among others, for a firm, an industry, a sector of the economy or the total economy. The objective of forecasting is to assist management to plan requirements for marketing efforts, materials, personnel, production services, capital acquisition and construction and finances. Wise, educated, and well-prepared forecasts should be accurate enough to allow for better planning and control than could be accomplished without the forecast.

There are several forecasting methods, some relatively simple, others complex and sophisticated in nature. During forecasting the historical data are analysed in order to identify a pattern that can be used to describe the time series. Then, this pattern is extrapolated or extended, into the future in order to prepare a forecast. The validity of forecasting depends on the assumption that the pattern that has been identified will continue in the future. A forecasting technique cannot be expected to give good predictions unless the assumption is valid. If the data pattern that has been identified does not persist in the future, this indicates that the forecasting technique is likely to produce inaccurate predictions. Changes in the pattern of the data should be monitored so that appropriate changes in the forecasting system can be made before the prediction can be considered accurate.

2.3 Time Series Analysis and Forecasting

Time series analysis and its applications have become increasingly important in various fields of research, such as business, economics, engineering, medicine, environometrics, social sciences, politics, and others. Since Box and Jenkins (1970, 1976) published the seminal book Time Series Analysis: Forecasting and Control, a number of books and a vast number of research papers have been published in this area.

The use of computers and computer software is essential in any modern quantitative analysis, even more so in time series analysis where complex algorithms and extensive computations are often required. With the speed and capacity of modern computers, in many situations it is preferable to adopt a methodology that simplifies the means of conducting an analysis even if it is at the expense of computation time. Using such an approach, we are able to provide simplified and effective methodologies for complex subjects in time series analysis and forecasting.

2.3.1 Definition

Anderson, Sweeney and Williams (2003) defined time series as a set of observations of a variable measured at successive points in time or over successive periods of time. Bowerman and 0'Connell (2003) defined time series as a set of observation of a variable of interest that has been collected in time order. Sincich (1991) defines time series as a collection of data obtained by observing a response variable on a regular chronological basis.

Time Series is a time dependent sequence. Y_1, Y_2… Y_n or $\{Y_t\}$, where $t \in N$, and 1,2,…,n denote time steps. Examples of time series are, monthly record of inflation in Ghana, monthly rainfall figures in Ghana, data on annual sales for a company, and the records of daily closing price of a stock at a stock exchange.

2.3.2 Deterministic Time Series

If the time series can be expressed as a known function then it is said to be deterministic, that is $Y_t = f(t)$

2.3.3 Stochastic Time Series

If a time series can be expressed as $Y_t = X(t)$, where X is a random variable then $\{Y_t\}$ is a stochastic time series.

2.4 Objectives of Time Series Analysis

There are several possible objectives in analysing a time series. These may be classified as description, explanation, prediction and control.

2.4.1 Description

The first step in analysing a time series data is usually to plot the data to obtain simple descriptive measures of the main properties of the series such as seasonal effect, trend effects and cyclic variation.

2.4.2 Explanation

When observations are taken on two or more variables it may be possible to use the variation in one time series variable to explain the variation in other time series variable. This may lead to a deeper understanding of the mechanism that generated the time series. For instance it is of interest to know how sales are affected by price and economic conditions.

2.4.3 Control

When a time series is generated which measures the quality of a manufacturing process, the aim of the analysis may be to control the process. Control procedures are of several different kinds.

In statistical quality control for instance, the observations are plotted on control charts and the controller takes action as a result of studying the charts. Box and Jenkins (1976) have described a more sophisticated control strategy which is based on a stochastic model to the series from which future values of the series are predicted. The values of the process variables predicted by the model are taken as target values and the variables conform to the target values.

2.5 Components of a Time Series

Traditional methods of Time Series analyses generally decomposes the variation in a Time Series into four components namely, a seasonal component(S_t), a trend component(T_t), a periodic or cyclical component(C_t) and a random error or irregular component(I_t) at a particular period t. Seasonal components occur at regular intervals. Cyclical components usually have longer duration that varies from cycle to cycle. The trend and cycle component are customarily combined into a trend-cycle component (TC_t). The specific functional relationship between these components can assume different forms. Spiegel and Stephens (2004) indicate that these four components combine in multiplicative or additive fashion as follows:

$$Y_t = T_t \times C_t \times S_t \times I_t$$

$$Y_t = T_tC_t + S_t + I_t$$

Where Y_t represents the observed value of the time Series at time t

2.5.1 Periodic Component

This refers to recurring up-and-down movements around trend levels. These fluctuations can last from two to ten years or even longer measured from peak to peak or trough to trough If $Y_t = Y_{t+T} + e_t$, for all $t \in N$ then the time Series has a periodic component with period T.

2.5.2 Trend Component

Trend refer to upwards or downward movement that characterizes a time series over time. Thus trend reflects the long- run growth or decline in the time series. Trend movements can reflect or represent a variety of factors. For example, long-run movements in the sales of a particular industry might be determined by changes in consumer taste, increases in total population, and increases in per capita income. If $Y_t = \beta_t + e_t$, then there exist a linear trend with slope β.

2.6 Stationary Time series

A time series is said to be strictly stationary if the joint distribution of $Y_{t1},\ldots,Y_{tn}$ is the same as the joint distribution of $Y_{t1+T},\ldots,Y_{tn+T,}$ for all $t_{1+T},\ldots,t_{n+T}$. in other words shifting the time origin by an amount T has no effect on the joint distributions, which must therefore depend only on the intervals between $t_1,\ldots,t_n$.

Bowerman and 0'Connell (2003) stated that a time series is stationary if the statistical properties (for example, the mean and the variance) of the time series are essentially constant through time. If we have observed n values $Y_1, Y_2, \ldots, Y_n$ of a time series, we can use a plot of these values (against time) to help us determine whether the time series is stationary. If the n values seem to fluctuate with constant variation around a constant mean (or level), then it is reasonable to believe that the time series is stationary. If the n values do not fluctuate around a constant mean or do not fluctuate with constant variation, then it is reasonable to believe that the time series is nonstationary

A stationary time series has finite variance, correlations between observations that are not time-dependent, and a constant expected value for all components of the time series (Brockwell and Davis 1991, p. 12).

2.6.1 Achieving stationarity

If there is a trend in the mean then differencing the time series data will remove the trend and stationarity will be achieved. For non-seasonal data, first-order differencing is usually sufficient to attain stationarity so that the new series Z_1, Z_2, …, Z_{n-1} is formed from the original series. $Z_t = Y_t - Y_{t-1} = \nabla Y_t$. Occasionally second- order differencing is used. If there is trend in variance, the series is made stationary by transforming the data as follows. $Z_t = ln Y_t$. Stationarity can also be achieved by taking the square root or the quartic root of Y_t. Other suitable methods also exist

2.7 Moving Average

A moving average is a trend method where each point of a moving average of a time series is the mean of a number of consecutive observations of the series. Moving averages are often used to forecast low trend items. Mathematically,

$$\text{Moving average} = \frac{\sum(\boldsymbol{most\ recent\ n\ data\ values})}{\boldsymbol{n}}$$

2.8 Autocorrelation Function

The autocorrelation coefficient, measures the degree of correlation between neighbouring observations in a time series. The autocorrelation coefficient at lag k is defined as;

$$\rho_k = \frac{E[(Y_t - \mu_Y)(Y_{t+k} - \mu_Y)]}{[E(Y_t - \mu_Y)^2 (Y_{t+k} - \mu_Y)^2]^{1/2}} \quad \text{and}$$

$$\rho_k = \frac{\text{cov}(Y_t, Y_{t+k})}{\sigma_{Y_t} \sigma_{Y_{t+k}}}$$

Where ρ_k is the autocorrelation function, μ is the population mean and σ is the population variance. The autocorrelation coefficient is estimated from the sample observations using the formula; $r_k = \dfrac{\sum_{t=2}^{n} (Y_t - \overline{Y}_t)(Y_{t+k} - \overline{Y}_{t+k})}{\sqrt{\sum_{1}^{n} (Y_t - \overline{Y}_t)^2} \sqrt{\sum_{2}^{n} (Y_{t+k} - \overline{Y}_{t+k})^2}}$

Jeffrey (1990) explained that the subscript limits in the numerator and the denominator leads to statistical difficulties, so a simplifying assumption is made. The series Y_t is assumed to be stationary, in both the mean and the variance. Thus the two means $\overline{Y}_t$ and $\overline{Y}_{t+k}$ is assumed to be equal. Therefore $\overline{Y}_t = \overline{Y}_{t+k} = \overline{Y}$, and the two standard deviations are estimated once using all the known data for Y_t. Using these assumptions the sample autocorrelation becomes

$$r_k = \frac{\sum_{t=2}^{n+k} (Y_t - \overline{Y})(Y_{t+k} - \overline{Y})}{\sum_{t=1}^{n} (Y_t - \overline{Y})^2}$$

Bowerman and 0'Connell (2003) define the sample autocorrelation function (SACF) to be a listing, or graph, of the sample autocorrelation at lags k =1, 2, ...

2.8.1 The Sampling Distribution of Autocorrelation coefficients

The autocorrelation coefficients of a random data are approximately normal with mean

$\mu_{pk} = 0$ and $\sigma_{pk} = \frac{1}{\sqrt{n}}$ where n is the sample size. J Jeffrey argued that, if r_k is the estimate of ρ_k then we can use our knowledge of normal distribution to make interval estimates of the population autocorrelation coefficient ρ_k. Thus for a random sample of size n = 40, say, we expect 99.73% of the sample autocorrelation coefficient to lie in the interval $-3\sigma_k \le r_k \le 3\sigma_k$. Similarly 95.45% of all sample autocorrelation lie in the interval $-2\sigma_k \le r_k \le 2\sigma_k$, and 68% lie in the interval $-\sigma_k \le r_k \le \sigma_k$. At what risk level are we willing to conclude that the data are not random when in reality they are. Stated differently, if we are willing to accept significance limit of two standard errors of the mean (95.45%) , the data can be concluded to be random if the sample autocorrelation coefficients are within the limits $-2\sigma_k \le r_k \le 2\sigma_k$, i.e. $\frac{-2}{\sqrt{40}} \le r_k \le \frac{2}{\sqrt{40}}$ which equals $-0.316 \le r_k \le 0.316$. Hence any value of r_k lying outside this interval is said to be significantly different from zero. This can also be achieved using the sample autocorrelation function SACF

2.9 Partial autocorrelation function

Partial autocorrelation measures the correlation between Y_t and Y_{t+k} when the effect of other time lags on Y_t are held constant. The partial autocorrelation is denoted by Φ_{kk}, k = 1, 2, …. The set of partial autocorrelation at various lags k are defined by $\phi_{kk} = \frac{|p_k^*|}{|p_k|}$, where ρ_k is the $k\times k$ autocorrelation matrix, and p_k^* is ρ_k with the last column replaced by $[\rho_1, \rho_2, \ldots, \rho_k]^T$ and

$$p_k = \begin{bmatrix} 1 & \rho_1 & \rho_2 & . & . & . & \rho_{k-1} \\ \rho_1 & 1 & \rho_1 & . & . & . & \rho_{k-2} \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ \rho_{k-1} & \rho_{k-2} & \rho_{k-3} & . & . & . & 1 \end{bmatrix}$$

So $\phi_{11} = \phi_1 = \rho_1$ and $\phi_{22} = \dfrac{\begin{vmatrix} 1 & \rho_1 \\ \rho_1 & \rho_2 \end{vmatrix}}{\begin{vmatrix} 1 & \rho_1 \\ \rho_1 & \rho_1^2 \end{vmatrix}}$ and estimates of Φ_{kk} can be obtained by replacing the ρ_1 by r_1.Bowerman and 0'Connell (2003) define the sample partial autocorrelation function (SPACF) to be a listing, or graph, of the sample partial autocorrelation at lags k = 1, 2, ...

2.9.1 Sampling distribution of the Partial Autocorrelation Coefficients.

The partial autocorrelation coefficients of a random data are approximately normal with $\mu_{\Phi kk} = 0$ and $\sigma_{\phi kk} = \dfrac{1}{\sqrt{n}}$. By similar argument as that for the sample autocorrelation, thus for a random sample of size n = 252, say, we expect 99.73% of the sample partial autocorrelation coefficient to lie in the interval $-3\sigma_{\phi kk} \le \phi_{kk} \le 3\sigma_{\phi kk}$. Similarly 95.45% of all sample partial autocorrelation lie in the interval $-2\sigma_{\phi kk} \le \phi_{kk} \le 2\sigma_{\phi kk}$, and 68% lie in the interval $-\sigma_{\phi kk} \le \phi_{kk} \le \sigma_{\phi kk}$. At what risk level are we willing to conclude that the data are not random when in reality they are. Stated differently, if we are willing to accept significance limit of two standard errors of the mean (95.45%) , the data can be concluded to be random if the sample partial autocorrelation coefficients are within the limits $-2\sigma_{\phi kk} \le \phi_{kk} \le 2\sigma_{\phi kk}$, i.e.

$\frac{-2}{\sqrt{252}} \le \phi_{kk} \le \frac{2}{\sqrt{252}}$ which equals $-0.126 \le \phi_{kk} \le 0.126$. Hence any value of ϕ_{kk} lying outside this interval is said to be significantly different from zero. This can also be achieved using the sample partial autocorrelation function SPACF.

2.10 An Autoregressive Model of order *p*. AR (*p*).

An autoregressive model is a special kind of regression model in which the explanatory variables are past values of the process. These values are called lags or lag values. A process that depends on p lags is called AR (p). An autoregressive model of order p is given by: $Y_t = \sum_{k=1}^{p} \alpha_k Y_{t-k} + \mu + e_t$ where μ is the mean of the time series data, α_k (k =1,2,…,p) are the coefficients called parameters, to be estimated, and e_t is a white noise. The order of an AR (p) process can be determined by the partial autocorrelation function (PACF). An AR(p) process has its PACF cutting off after lag p and the ACF decays. One important fact about autoregressive models is that it is possible to obtain a simple set of linear equations that expresses the parameters of the model in terms of the auto correlations and the variance of the data. These linear equations are called the Yule-Walker equations, given as

$$\rho_k = \alpha_1 \rho_{k-1} + \alpha_2 \rho_{k-2} + ... + \alpha_p \rho_{k-p}$$

The parameters can also be estimated using the method of ordinary least squares.

2.11 Moving Average Model of order *q*. MA (*q*).

The moving average (MA) models provide predictions of Y_t based on a linear combination of past forecast errors. A MA model of order q is given b

$Y_t = \sum_{k=1}^{q} \theta_k e_{t-k} + \mu + e_t$ where μ is the mean of the time series data. θ_k (k=1,2,…,q) are coefficients called parameters to be estimated, and the order q refers to the number of parameters .

2.12 Causes of inflation

The factors that cause inflation in an economy can be categorized into two, namely,

(i) Demand pull factors and

(ii) Cost push factors

It should be noted that, based on these categorization economist also distinguish between demand pull inflation and cost push inflation. The demand pull factors are the factors that create excess demand for goods and services in an economy. For instance, excess demand for a good or service will lead to increase in the price of that good or service. If we keep on experiencing excess demand for goods and services, then prices of goods and services will keep on changing hence resulting in inflation.

Demand pull factors mostly mentioned are increases in government spending and increases in money supply. If government increases its spending, individuals will have more money and want to spend it on goods and services. This will lead to an increase in demand for goods and services and if there is no corresponding increase in supply, it will lead to inflation. Increases in money supply will also have similar effects. If the central bank increases money supply, it will create excess money in the system and economic agents would want to spend the excess money on goods and services. If we don't have a corresponding increase in supply of goods and services, it will create a situation which is usually referred to as "more money chasing few goods". In other words the increase in money supply will lead to excess demand of goods and services and the result is an increase in the price of goods and services. As a result of these factors inflation in most cases is termed a monetary phenomenon.

The cost push factors are the factors that lead to a rise in the cost of production of goods and services. In other words they are factors that create shortage of goods and services

in an economy. A reduction in the production of goods and services due to high cost of production will also create excess demand for goods and services which will lead to increase in the prices of goods and services. If this situation continues then prices of goods and services will keep on rising and can result in inflation. Some of the cost push factors that are worth mentioning are increase in nominal wages and salaries, increases in cost of inputs and occurrence of natural disasters such as the one that happened in the northern part of Ghana in 2007.These factors lead an increase in the per unit cost of production. The increase squeezes profit and reduces the amount of output firms are willing to supply at existing price level. As a result the supply of goods and services in the economy decline and eventually drive up prices of goods and services.

2.13 Cost of Inflation

2.13.1. Inflation and individuals on fixed income

To understand the impact of inflation on individuals on fixed income, it is imperative for one to understand the difference between nominal and real income. The nominal income is the amount of money received as wages, rent, interest or profit while real income measures the amount of goods and services nominal income can buy. This is also known as purchasing power of income. Real income is obtained by dividing nominal income by the price level. This means that if nominal income increases faster than the price level, real income will rise, however if the price level increases faster the nominal income then real income will decline. Given nominal income, inflation will result in a reduction in real income. This means that, with fixed nominal income, inflation will result in the reduction in the amount of goods and services that people can buy that is a reduction in the purchasing power which also means a reduction in the materials standard of living of individuals on fixed income.

2.13 2 Inflation on borrowers and lenders

Inflation has negative impact on lenders and positive impact on borrowers. In this direction inflation is said to redistribute income from the rich to the poor. In times of inflation those who lend money lose in real terms while those who borrow money gain in real term.

2.13.3 Inflation and store of value

In periods where we have high inflation, individuals do not store their wealth in the form of cash, but rather stored in the form of fixed assets such as land and buildings. The reason is that, inflation result in lost of value of wealth stored in cash. Hence individuals would want to store their wealth in other forms that are not affected by inflation.

2.13.4. Inflation and price system

Inflation may also result in situations where people will be quoting the price of their commodities in foreign currencies. In periods of high inflation the domestic currency loses its value compared with stable foreign currency. Individuals will want to quote the prices of commodities in the stable currency. A typical example of this happened in Ghana in the early 1990's and was referred to as the dollarization of the economy. Goods and services especially rent were quoted in foreign currency.

2.14 Inflation and the Economy of Ghana

Inflation therefore has an enormous effect on an economy and Ghana is not an exception. Inflation can affect the economy of Ghana in the following ways:

(i) Reduction in the real value of savings

(ii) Disruption of business plan

(iii) Currency substitution

(iv) Fall in international competitiveness

(v) Redistributive effect

(vi) Distortion in price mechanism

(vii) Manu cost

(viii) Higher wage demand.

As the real value of income falls, households, firms and governments tend to spend more on goods and services thereby saving less or none Secondly, businesses or firms tend to review their business plans every now and then when there is a persistent rise in the general price levels of goods and services. Thirdly, currency substitution is paramount during inflation. That is other currencies are compared with the Ghanaian cedi in times of inflation hence a situation normally known as dollarization occurs. In addition, fall in international competitiveness is another effect of inflation on the economy of Ghana. Commodities and services from Ghana when found in the external market tend to be of higher prices hence less competitive to those with lower prices from other countries. Also, redistributive effect of inflation tends to close the gap between the rich and the poor in a way. That is borrowers tend to gain at the expense of lenders. Furthermore, prices of commodities and services become unstable during inflation. That is the rise and fall in the general price levels brings about distortion in the price mechanism .Also, in times of inflation restaurants has to revisit their menu list frequently to make the necessary adjustment in prices hence the cost of reprinting. Finally, another major effect of inflation on the economy of Ghana is the scramble for higher wages by public sector workers. In times of inflation the real income of workers falls. This makes workers to fight for higher wages to meet their daily expenditure.

In succinct the effects of inflation on the economy of Ghana bring about poor standard of living, high unemployment rate and low-level economic growth and development. Therefore the government of Ghana in other to curtail all these problems has to print more money or go for grants from its development partners and also the multilateral financial institutions.

2.15 Measurement of inflation

The most common measure of inflation is the consumer price index (CPI) over months, quarterly or yearly. The CPI measures changes in the average price of consumer goods and services. Once the CPI is known, the rate of inflation is the rate of change in the CPI over a period (e.g. month-on month inflation rate) with percentage being the standard unit.

2.16 Review of Inflation

Literature on inflation in Ghana is limited. The few available papers were mostly conducted during the economic reforms of the early 1980s and 1990s.Nonetheless, the limited amount of work can still be catalogued on the basis of the monetarist and the structuralist paradigm.Bawumia and Atta-Mensah(2003), using a vector error correction forecasting (VECF) model, conclude that inflation was a monetary phenomenon in Ghana. Their paper does not explore the potential for real factors in price determination.Dordunoo (1994) observe that rapid exchange rate depreciation and resultant hike in import prices were in themselves inflationary. In contrary, a school of thought championed by Chhibber and Shaffik (1991) holds the view that since most prices with the exception of petroleum prices were transacted at the parallel exchange rate, depreciation of the official exchange rate could not have affected inflation significantly.Chhibber and Shaffik(1991) demonstrated that devaluation was indeed ant inflationary. Their study used three transmission mechanisms, fiscal/monetary, cost-push factors and other real factors. These were represented in a single framework

A lot of researchers have investigated the relative accuracy of alternative inflation forecasting models. One approach has been to compare the accuracy of survey respondents inflation forecast relative to univariate time- series models

Another approach is the methodology associated with the work of Fama(1975,1977) and recently extended by Fama and Gibbons(1982,1984). This approach extracts from observed nominal interest rates the market's inherent expectation of inflation. Based on the univariate time series modelling of the real interest rate, Fama and Gibbons (1984) find that the interest rate model yields inflation forecasts with a lower error variance than a univariate model, and that the interest rate model's forecasts dominate those calculated from the Livingston survey.

Aiden Meyler, Geoff Kenny and Terry Quinn (1998) outlined autoregressive integrated moving average (ARIMA) time series models for forecasting Irish inflation. It considered two alternative approaches to the issue of identifying ARIMA models-the Box Jenkins approach and the objective penalty function methods. The emphasis is on forecast performance, which suggests that ARIMA forecast has outperformed. Geoff Kenny, Aidan Meyler and Terry Quinn (1998) focussed on the development of multiple time series models for forecasting Irish inflation. The Bayesian approach to the estimation of vector autoregressive (VAR) model is employed. This allows the estimated models combine the evidence in the data with any prior information, which may also be available. A large selection of inflation indicators is assessed as potential candidates for inclusion in a VAR. The result confirms the significant improvement in forecasting performance, which can be obtained by the use of Bayesian techniques.

Toshikata Sekine (2001) estimated an inflation function and forecasts one-year ahead inflation for Japan. He found that mark-up relationships, excess money and output gap are particularly relevant long-run determinants for an equilibrium correction model (Eq.CM) of inflation.

Tim Callen and Dongkoo Chang (1999) found that the Reserve Bank of India (RBI) has moved away from a broad money target toward a "multiple indicators" approach to the conduct of monetary policy. In adopting such a framework, it is necessary to know which of the many potential indicators provide the most reliable and timely information on future developments in the target variable(s).

Mohammed Abdus Salam, Shazia Salam and Mete Feridun (2007) in forecasting and modelling Pakistan's inflation using time series ARIMA models assesses which indicators provide the most useful information about future inflationary trends. They conclude that while the broad money target has been de emphasised, development in the monetary aggregates remain an important indicator of future inflation. The exchange rate and import prices are also relevant, particularly for inflation in the manufacturing sector.

Rangarajan (1998) also found that maintaining a reasonable degree of price stability while ensuring an adequate expansion of credit to assist economic growth have been the primary goals of monetary policy in India. The concern with inflation emanates not only from the need to maintain overall macroeconomic stability, but also from the fact that inflation hits the poor particularly hard as they do not possess effective inflation hedges. One may say that inflation is the single biggest enemy of the poor. Consequently, maintaining low inflation is seen as a necessary part of an effective anti-poverty strategy. By the standard of many developing countries, India has been reasonably successful in maintaining an acceptable rate of inflation. Since the early 1980's inflation has not exceeded 17 %(measured by the year-on year change in the monthly WPI and has averaged about 8%. While this is only at par with other countries in the Asia region.

Francisco Nadal-De Simone (2000) estimated two times –varying parameter models of Chilean inflation. Box-Jenkins models out perform the two models for short-term out-of-sample forecasts; their superiority deteriorates in longer forecasts.

Meyler, Kenny and Quinn (1998) have considered autoregressive integrated moving average (ARIMA) forecasting.ARIMA models are theoretically justified and can be surprisingly robust with respect to alternative (multivariate) modelling approaches. Indeed, Stockton and Glassman (1987, pg.117) upon finding similar results for the United States commented that “it seems somewhat distressing that a simple ARIMA model of inflation should turn in such a respectable forecast performance relative to the theoretically based specifications”

Ling and Li (1997) considered fractionally integrated autoregressive moving-average time series models with conditional heteroscedasticity, which combined the popular generalised autoregressive conditional heteroscedastic (GARCH) and the fractional (ARMA) models.

Drost and Klaassen (1997) said that it is well-known that financial data sets exhibit conditional heteroscedasticity. GARCH-type models are often used to model this phenomenon. They constructed adoptive and hence efficient estimators in a general GARCH in mean-type context including integrated GARCH models.

Aidoo and Eric (2010) in modelling and forecasting Ghana’s inflation rates using ARIMA Models also commented that an increase in world oil prices always leads to increase in Ghana’s inflation

Ocran (2007) in modelling Ghana’s inflation Experience, sought to ascertain the key determinants of inflation in Ghana for the past 40 years. Stylized facts about Ghana’s inflation experience indicates that since the country’s exit from the West African Currency Board soon after independence, inflation management has been ineffective despite two decades of vigorous reforms. Using the Johansen co integration test and an error correction model, the paper identified inflation inertia, changes in money, and changes in Government of Ghana treasury bill rates, as well as changes in the exchange rate, as determinants of inflation in the short run. Of these, inflation inertia is the dominant determinant of inflation in Ghana. It is therefore suggested that to make treasury bill rates more effective as a nominal anchor, inflationary expectations ought to be reduced considerably.

Fischer (1930) hypothesis reveals that inflation is the main determinant of interest rate since a one percent increase in the rate of inflation, result to a corresponding one percent increase in the interest rate.

Bailey (1956) argued that inflation has negative effects on the economy through it cost on welfare. He further stated that the costs associated with unanticipated inflation are: the distributive effects from creditors to debtors, increasing uncertainty affecting consumption, savings, and borrowing and investment decisions.

It is acknowledged that the above debate evolved from a controversial notion between the structuralist and the monetarists. This made Mundell (1965) to predict a positive relationship between the rate of inflation and the rate of capital accumulation, which in turn implies a positive relationship to the rate of economic growth. He argued that since money and capital are substitutable, an increase in the rate of inflation increases capital accumulation by shifting the portfolio from money to capital, thereby stimulating a higher rate of economic growth.

Conversely, Fischer and Modigliani (1978) suggested a negative and non-linear relationship between the rate of inflation and economic growth. Sargent and

Wallace (1981) in their contribution to the debate indicated an unpleasant monetarist arithmetic that, the more

increase in the cost of borrowing, the harder to finance this debt stock and the more condensed the expectations of economic agents for the possibility of monetization by money authority.

Espana, Senra and Albacete (2001) in forecasting inflation in the European Monetary Union also said that inflation in the European Monetary Union is measured by the Harmonised Indices of Consumer Prices (HICP) and it can be analysed by breaking down the aggregate index in two different ways. One refers to the breakdown into price indexes corresponding to big groups of markets throughout the European countries and another considers the HICP by countries. Both disaggregations are of interest because in each one, the component prices are not fully co integrated, having more than one common factor in their trends. The paper shows that the breakdown by group of markets improves the European inflation forecast and constitutes a framework in which general and specific indicators can be introduced for further improvements.

Rubens et al (1989) in their contribution to the debate also argues that inflation has become one of the predominant financial concerns of the late twentieth century. In the late 1970s, public opinion polls ranked inflation as the number one problem in the United States. While the rate of inflation has slowed since the late 1970s, inflation is still present and many investors expect a resurgence of inflation to higher levels in the near to immediate future. This continued concern about inflation has led to an increased search and evaluation of investments that will protect investors from inflation. Assets that have the ability to protect investors from the effects of inflation are generally labelled inflation hedges. Real estate has been regarded as one of the best inflation hedges of past years. While there has been research in the past evaluating this possibility and some recent research using only business real estate, no current research on residential real estate or farmland as inflation hedges exists. Their study examines the inflation-hedging effectiveness of residential real estate, farmland, and business real estate (with a different data set) as individual assets and in a portfolio context for 1960-86.

Kiley (2009) in Finance and Economic Discussion Series also argued that inflation expectations play a central role in models of the Phillips curve. At long time horizons inflation expectations may reflect the credibility of a monetary authority's commitment to price stability. These observations highlight the importance of inflation expectations for monetary policy. These comments touch on three issues regarding inflation expectations: The evolving treatment of inflation expectations in empirical Phillips curve models; three recent models of information imperfections and inflation expectations; and potential policy implications of different models

Beechey et al, (2008) compares the recent evolution of long-run inflation expectations in the euro area and the United States, using evidence from financial markets and surveys of professional forecasters. Survey data indicate that long-run inflation expectations are reasonably well-anchored in both economies, but also reveal substantially greater dispersion across forecasters' long-horizon projections of U.S. inflation. Daily data on inflation swaps and nominal-indexed bond spreads--which gauge compensation for expected inflation and inflation risk, also suggest that long-run inflation expectations are more firmly anchored in the euro area than in the United States. In particular, surprises in macroeconomic data releases have significant effects on U.S. forward inflation compensation, even at long horizons, whereas macroeconomic news only influences euro area inflation compensation at short horizons.

Mizen, (2003) argues that inflation-targeting central banks should announce explicit loss function with numerical relative weights on output-gap stabilization and use and announce optimal time-varying instrument-rate paths and corresponding inflation and output-gap forecasts. Simple voting procedures for forming the Monetary Policy Committee's aggregate loss function and time-varying interest-rate paths are suggested. Announcing an explicit loss function improves the transparency of inflation targeting and eliminates some misunderstandings of the meaning of ``flexible" inflation targeting. Using time-varying instrument-rate paths avoids a number of inconsistencies and other problems inherently associated with constant-interest-rate forecasts

Dornbusch and Fischer.(1993) in The World Bank Economic Review also said that inflation persists at moderate rates of 15 to 30 percent in all the countries that successfully reduced triple digit inflations in the 1980s. Several other countries, for example Colombia, have experienced moderate inflation for prolonged periods. Theories of persistent inflation can be classified into those that emphasize Seigniorage as a source of government finance and those that emphasize the costs of ending inflation. We examine the sources and persistence of moderate inflation episodes. Most episodes of moderate inflation were triggered by commodity price shocks and were brief; very few ended in higher inflation. This article presents case studies of eight countries, including three that now suffer from moderate inflation and four that successfully moved down to single-digit inflation rates. The roles of Seigniorage, indexation and disindexation, the exchange rate commitment, and monetary and fiscal policy are examined. The evidence suggests that Seigniorage plays no more than a modest role in the persistence of moderate inflations and that such inflation can be reduced only at a substantial short-term cost to growth.

Fritzer et al, (2002) evaluate the performance of VAR and ARIMA models to forecast Austrian HICP inflation. Additionally, they investigate whether disaggregate modelling of five subcomponents of inflation is superior to specifications of headline HICP inflation. their modelling procedure is to find adequate VAR and ARIMA specifications that minimise the 12 months out-of-sample forecasting error. The main findings are twofold. First, VAR models outperform the ARIMA models in terms of forecasting accuracy over the longer projection horizon (8 to 12 months ahead). Second, a disaggregated approach improves forecasting accuracy substantially for ARIMA models. In case of the VAR approach the superiority of modelling the five subcomponents instead of just considering headline HICP inflation is demonstrated only over the longer period (10 to 12 months ahead).

Gómez and Maravall, (1998) also used a unified approach to automatic modelling for univariate series is presented. First, ARIMA models and the classical methods for fitting these models to a given time series are reviewed. Second, some objective methods for model identification are considered and some algorithmical procedures for automatic model identification are described. Third, outliers are incorporated into the model and an algorithm, for automatic model identification in the presence of outliers is proposed.

Reijer and Vlaar, (2003), in their study build two forecasting models to predict inflation for the Netherlands and for the euro area. Inflation is the yearly change of the Harmonised Index of Consumer Prices (HICP). The models provide point forecasts and prediction intervals for both the subcomponents of the HICP and the aggregated HICP-index itself. Both models are small-scale linear time series models allowing for long run equilibrium relationships between HICP subcomponents and other variables, notably the hourly wage rate and the import prices. The model for the Netherlands is used to generate Dutch inflation forecasts over a horizon of 11-15 months ahead for the Narrow Inflation Projection Exercise (NIPE). NIPE-forecasts have been generated quarterly by each country in the euro system since 1999.

Bruneau, et. al.,(2003).In order to provide short run forecasts of headline and core HICP inflation for France, we assess the forecasting performance of a large set of economic indicators, individually and jointly, as well as using dynamic factor models. We run out-of-sample forecasts implementing the Stock and Watson (1999) methodology. It turns out that, according to usual statistical criteria, the combination of several indicators -in particular those derived from surveys- provides better results than dynamic factor models, even after pre-selection of the variables included in the panel. However, factors included in VAR models exhibit more stable forecasting performance over time. Results for HICP excluding unprocessed food and energy are very encouraging. Moreover, they show that it is possible to use forecasts on this indicator to project overall inflation.

Tse, (1997), in modelling real estate prices using ARIMA said technical analysis lies on the premises that short-term market price at any time is revealed by pattern of prior price movements. Tests empirically the pattern of the real estate prices by employing the ARIMA analysis. Results strongly show that there exist cyclical trends in the office and industrial property prices in Hong Kong. The forecasting method can provide an indication of short-term market direction, a sense of whether or not the movement will be small or large, and advance warning well ahead of any turning points supplementary to investment strategy. The investor may wish to incorporate forecasts from an ARIMA model into his investment strategy, for timing purposes.

In another development Cati, et al., (1999) used a standard unit root test for the Brazilian case from the period between January 1974 and June 1993.They realized that the series are stationary and the observed perturbations have temporary effect. The conclusion was that macroeconomic interpretation of the results are in line with the inflationally inertia hypothesis. In relation to the above Chan (1999), adopted the multiple time- series modelling approach suggested by Tiao and Box (1981) to construct a stochastic investment model for price inflation and share dividends. They observed that the method has the advantage of being direct and sequential with respect to iterative steps of tentative specification, estimation and diagnostic checking, parallel to those of the well-known Box-Jenkins method in the univariate time-series analysis. It does not specify any prior causality as compared to those of other stochastic asset models in the literature. Fari and Carneiro (2001) also used the vector auto regression (VAR) to analyze a bivariate time series model for the annual Brazilian data from the period of 1980 to 1995. They concluded that, there exist a negative relationship between inflation and economic growth in the short run, whilst it does not affect economic growth in the long run.

2.17 Application of ARIMA Models to forecast Inflation

ARIMA models have been used to forecast inflation in many countries all over the world. The following are instances of its use. Aidoo (April, 2010) use the Box-Jenkins Seasonal Autoregressive Integrated Moving Average (SARIMA) approach to analyse monthly inflation rate of Ghana from July 1991 to December 2009. His study mainly intended to forecast the monthly inflation rate for the period of January, 2010 to July 2010.Based on minimum AIC, AIC_c and BIC value, the best-fitted SARIMA models tend to be ARIMA$(1,1,1)(0,0,1)_{12}$ and ARIMA$(1,1,2)(0,0,1)_{12}$ models. After the estimation of parameters of selected models, a series of diagnostic and forecast accuracy test were performed. Having satisfied all the model assumptions, ARIMA $(1, 1, 1)(0,0,1)_{12}$ model was judge to be the best model for forecasting. The predicted monthly inflation rates were consistent with the actual values.

Conclusion: The forecasting results in general revealed a decreasing pattern of inflation rate over the forecasted period and turning at the month of July. The author confirmed that ARIMA model fit the data better and forecast inflation rate with high prediction precision in the short-term.

Owusu (2010) also attempt to outline the practical steps which needed to be undertaken in order to use the autoregressive integrated moving average(ARIMA) model for forecasting Ghana's inflation. The main focus of the study is to model inflation and hence used to forecast the monthly inflation on the short-term basis. For this purpose, different ARIMA models are used and the candid model is selected based on various diagnostic, evaluation and selection criteria. He concluded that the model has sufficient predictive powers and the findings are well in line with those of other studies. Again the study models inflation for the periods of 1990 to 2000 and 2001 to 2009 and it was realized that the inflation model for the

period of 1990 to 2000 is ARIMA (1, 2, 2) written as $\hat{y}_t = 18.5770 + 0.455848t - 3.57e^{-0.3}t^2 + 0.7807y_{t-1} - 1.0813\varepsilon_{t-1} + 0.1020\varepsilon_{t-2} + \hat{\varepsilon}_t$.Whilst that of 2001 to 2009 is modelled as ARIMA (2,2,1), written as $\hat{y}_t = 34.3958 - 0.637228t + 4.40e^{-0.3}t^2 - 1.3764y_{t-1} - 0.4389y_{t-2} + 0.9860\varepsilon_{t-1} + \hat{\varepsilon}_t$.It was concluded that inflation for the period of January 2001 to December 2009 was less than that of January 1990 to December 2000. The model is recommended for use by stakeholders because it has a lower error variance of ±1 which follows closely with the actual data.

The intent of this chapter is to review relevant literature of time series and forecasting, literature on inflation such as definition of inflation, causes of inflation, cost of inflation, measurement of inflation and application of ARIMA models to forecasting inflation, and we opened a new chapter which is titled the methodology.

CHAPTER 3

METHODOLOGY

3.1 Box-Jenkins Approach to Forecasting:

In this chapter the methodology and the theorems propounded by Box and Jenkins called the Autoregressive Integrated Moving Average (ARIMA) was extensively explored. This is an advance forecasting technique that takes into account historical data and decomposes it into an Autoregressive (AR) process, where there is a memory of past values, an Integrated (I) process, which accounts for stabilizing or making the data stationary plus a Moving-Average(MA) process, which accounts for previous error terms making it easier to forecast.

3.2 Autoregressive Moving Average Process (ARMA) or Mixed Process.

According to Jeffrey (1990), autocorrelation patterns may require more complex models. A more General model is a mixture of the AR(p) and MA(q) models and is called autoregressive moving-average model, ARMA(p,q) model . He explained further that this model forecasts Y as both a linear combination of actual past values and a linear combination of past errors. The general ARMA (p,q) model is given by

$$Y_t = \mu + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + ... + \alpha_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - ... - \theta_q e_{t-q} \qquad (1)$$

$$Y_t = \sum_{k=1}^{p} \alpha_k Y_{t-k} - \sum_{k=1}^{q} \theta_k e_{t-k} + \mu + e_t \qquad (2)$$

Like the AR (p) model, the ARMA (p, q) , has autocorrelation that diminish as the distance between residuals increases. However the patterns in the time series that can be described by the ARMA (p, q) process are more general than those of either AR (p) or MA (q) models. Mixed ARMA process has theoretical ACFs with both AR and MA characteristics. In practise; p and q are usually not greater than 2 in an

ARMA model for non seasonal data. The PACF for the same model tails off to zero rather than cutting off after one or two lags. This is an important characteristic of ARMA models. Neither the ACF nor PACF cut off on mixed ARMA models. Finally, it has been found that most of the stationary time series occurring in practice can be fitted by AR(1), AR(2), MA(1), MA(2), ARMA(1,1) or white noise models. Hence these six models are the only time series that are commonly used in practice.

3.3. Estimating the Parameters of an ARMA Model

The procedure for estimating the parameters of the ARMA model is like the one for the MA model as described above, it is an iterative method. Like the MA the residual sum of squares is calculated at every point on a suitable grid of the parameter values, and the values which give the minimum sum of squares are the estimates.

3.4 The Autoregressive Integrated Moving Average Model (ARIMA)

If a non stationary time series which has variation in the mean is differenced to remove the variation the resulting time series is called an integrated time series. The original series is referred to as an ARIMA model. The term integrated is used when differencing is performed to achieve stationarity, since the stationary series must be integrated (undifferenced) to recover the original data. In practice most time series encountered are non stationary and the series is differenced to obtain stationarity. The resulting series may require only an AR component p, or an MA component q, or a mixed ARMA component. These models are called autoregressive integrated (ARI) or integrated moving average (IMA) or Autoregressive Integrated Moving Average (ARIMA) Model. Notationally, all AR(p) and MA(q) models can be represented as ARIMA models. The general model is ARIMA (p,d,q). The order of an ARIMA model is given by the three letters p,d,q. The order of the autoregressive component is p, the order of differencing needed to achieve stationarity is d, and the order of the moving average component is q. In general the ARIMA process is of the form

$$Z_t = \sum_{k=1}^{p} \alpha_k Z_{t-k} - \sum_{k=1}^{q} \theta_k e_{t-k} + \mu + e_t \tag{3}$$

3.5 The backshift and difference operators for ARIMA representation.

To express and understand differenced ARIMA models the concept of the backshift (lag) operator, B, and difference operator, ∇, is used, These has no mathematical meaning other than to facilitate the writing of different type of models that would otherwise be extremely difficult to express. The backshift is defined as $B^m Y_t = Y_{t-m}$. For example $BY_t = Y_{t-1}$,

$B^2 Y_t = Y_{t-2}$, and $B^{12} Y_t = Y_{t-12}$. The difference operator takes the form $\nabla^d = (1-B)^d$, when d differences are taken to achieve stationarity in the time series data. Using these notations,

1. The general AR(p) model $Y_t = \sum_{k=1}^{p} \alpha_k Y_{t-k} + \mu + e_t$ is expressed as $Y_t - \alpha_1 Y_{t-1} - \alpha_2 Y_{t-2} - \ldots - \alpha_p Y_{t-p} = \alpha(B) Y_t = e_t + \mu$, where $\alpha(B)$ is the autoregressive operator of order p, defined by

$$\alpha(B) = 1 - \alpha_1 B - \alpha_2 B^2 - \ldots - \alpha_p B^p \tag{4}$$

2. The general MA(q) model $Y_t = \sum_{k=1}^{q} \theta_k e_{t-k} + \mu + e_t$ is expressed as $Y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} = \theta(B) e_t + \mu$, where $\theta(B)$ is the moving average operator of order q, defined by $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$ (5)

3. The general ARMA(p,q) model, $Y_t = \mu + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q}$, is expressed as

$$Y_t - \alpha_1 Y_{t-1} - \alpha_2 Y_{t-2} - \ldots - \alpha_p Y_{t-p} = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} + \mu$$
$$(1 - \alpha_1 B - \alpha_2 B^2 - \ldots - \alpha_p B^p) Y_t = (1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q) e_t + \mu$$

$$\alpha(B) Y_t = \theta(B) e_t + \mu \tag{6}$$

4. Stationary series Z_t obtained after d differencing of Y_t is given by

$$Z_t = \nabla^d Y_t = (1 - B)^d Y_t \tag{7}$$

5. A general ARIMA(p ,d, q) model is expressed

$$(1 - B)^d (1 - \alpha_1 B - \alpha_2 B^2 - \ldots - \alpha_p B^p) Y_t = (1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q) e_t$$
$$(1 - B)^d \alpha(B) Y_t = \theta(B) e_t \tag{8}$$

3.6 Estimating the Parameters of an ARIMA model.

In practice most time series encountered are non stationary and the series is differenced to obtain stationarity. The resulting series may require only an AR component p, or an MA component q, or a mixed ARMA component. These models are called autoregressive integrated (ARI) or integrated moving average (IMA). The procedures for the estimation of the parameters of the differenced series of the fitted models are as described for the AR(p), MA(q) and ARMA(p, q) earlier.

3.7 Identifying General Time Series Models.

The table below gives the summary of the general non seasonal time series models and their statistical properties. The table summarizes discussions on general AR, MA, and mixed ARMA models. Conditions for stationarity and invertibility required by each model and a description of the behaviour of the theoretical ACF and PACFs for each model.

Table 3.1: General Time Series Models

MODEL	STATIONARITY CONDITION	INVERTIBILITY CONDITION	ACF COEFFICIENTS	PACF COEFFICIENTS
AR(p)	Yes	No	Dies down	Cuts off after lag p
MA(q)	No	Yes	Cuts off after lag q	Dies down
ARMA(p,q)	Yes	Yes	Dies down	Dies down

3.8 Seasonal Autoregressive Integrated Moving Average Model (SARIMA)

It has been noted earlier in this study that the study of autocorrelation can provide adequate indications of the relative importance of a seasonal pattern in a data. We may find it desirable to forecast seasonal series that are unadjusted for seasonality. Seasonality varies from year to year, indicating that the models based on the unadjusted rather than seasonally adjusted data are likely to be more flexible and useful. If changing seasonality is expected, it is usually preferable to account for it through the development of a properly specified ARIMA model.

For time series that contain a seasonal component that repeats every *s* observations, a supplement to the non seasonal ARIMA model can be applied. For a seasonal time series data with period *s*, Seasonal ARIMA $(P, D, Q)^s$ models can be developed in a manner similar to ordinary ARIMA process. s = 12 for monthly data and *s* = 4 for quarterly data. In a multiplicative seasonal ARIMA (SARIMA) model the regular and seasonal autoregressive components, differences, and moving average components are multiplied together in the general model. Often most of the p, d, q values are zero in practical illustration and the resulting models are often quite simpler and parsimonious. A very useful notation for describing the orders of the various components in the multiplicative model is given by $(p, d, q) \times (P, D, Q)^s$, with p, d, q having their usual meaning and P is the order of the seasonal AR process, D the order of the differencing of the seasonal process, and Q the order of the seasonal MA process, and *s* is the order of seasonality. By representing a time series by a multiplicative model it is often possible to reduce the number of parameters to be estimated. Also it aids in interpreting the model structure Jeffrey (1990), explained that in studying seasonal data, an ARMA process may consist of two parts; the regular portion and the seasonal portion. For the purpose of identifying a seasonal ARMA process, we divide the process into two parts. To identify the seasonal pattern, we ignore the non seasonal process and determine whether the seasonality is determined by an AR or MA process by focusing on the coefficient on the seasonal terms.

3.9 Seasonal Autoregressive Models.

A purely seasonal time series is the one that has only seasonal AR or MA parameters. Seasonal autoregressive models are built with parameter called seasonal autoregressive (SAR) parameters. The SAR parameters represent the autoregressive relationships that exist between time series data separated by multiples of the number of periods per season. A general AR model with P SAR parameters is given by $Y_t = \sum_{i=1}^{p} \alpha_{is} Y_{t-is}$ where Y_{t-s} is of order *s*, Y_{t-2s} is of order 2*s* and Y_{t-ps}, is of order *ps*. A model with one SAR parameter is written as $Y_t = \alpha_s Y_{t-s} + e_t$ (9)

3.10 Seasonal Moving Average Models

Seasonal moving Average models are built with seasonal moving average (SMA) parameters. SMA parameters represent moving average relationship that exists among time series observations separated by a multiple of the number of periods per season. The general SMA model with Q parameters is given by

$$Y_t = \sum_{i=1}^{Q} \theta_{is} e_{t-is} + e_t \tag{10}$$

3.11 Mixed SAR and SMA Models

The general mixed SAR and SMA model is given by

$$Y_t = \sum_{i=1}^{P} \alpha_{is} Y_{t-is} + \sum_{i=1}^{Q} \theta_{is} e_{t-is} + e_t \tag{11}$$

The order the seasonal ARMA process is given in terms of both P*s* and Q*s*

3.12 Identifying the Seasonal ARMA Model

For pure SAR models, the autocorrelation function dies down and the partial autocorrelation function cuts off after one seasonal lag for a SAR (1) model. Similarly the partial autocorrelations die down for SMA models. Also the autocorrelation function cut off after one seasonal lag for SMA (1) model and after two seasonal lags for SMA (2). For the mixed seasonal ARMA with one SAR and one SMA both the autocorrelation function and partial auto correlation functions die down. The table below gives the summary of the stationarity and invertibility conditions of some specific seasonal time series models and the behaviour of their theoretical ACF and PACF.

Table 3.2: Specific Pure Seasonal Time Series Models

ARMA MODEL	STATIONARITY CONDITION	INVERTIBILITY CONDITION	ACF COEFFICIENTS	PACF COEFFICIENTS
$(1,D,0)^s$	$-1 < \alpha_s < 1$	none	Dies down	Cuts off after one seasonal lag
$(2,D,0)^s$	$\alpha_s + \alpha_{2s} < 1$ $\alpha_s - \alpha_{2s} < 1$ $-1 < \alpha_{2s} < 1$	none	Dies down	Cuts off after two seasonal lag
$(0,D,1)^s$	None	$-1 < \theta_s < 1$	Cuts off after one seasonal lag	Dies down
$(0,D,2)^s$	None	$\theta_s + \theta_{2s} < 1$ $\theta_{2s} - \theta_s < 1$ $\theta_{2s} < 1$	Cuts off after two seasonal lag	Dies down
$(1,D,1)^s$	$-1 < \alpha_s < 1$	$-1 < \theta_s < 1$	Dies down	Dies down

3.13 Box-Jenkins Methods and ARIMA Modelling

The Box-Jenkins methodology, (Box and Jenkins, 1976) is a statistically sophisticated way of analysing and building a forecasting model which best represents a time series. This technique has a number of advantages over other methods of time series analysis. Firstly, it is logical and statistically accurate. Secondly the method extracts a great deal of information from the historical time series data. Finally, the method results in an increase in forecast accuracy while keeping the number of parameters to a minimum in comparison with similar modelling process.

To begin with the methodology assumes no particular pattern in the historical data of the time series to be forecast. The first stage is the identification of the appropriate ARIMA models through the study of the autocorrelation and partial autocorrelation functions. The next stage is to estimate the parameters of the ARIMA model chosen. The third stage is the diagnostic checking of the model. The Ljung-Box chi-square statistic, called the Q statistic is used to check the model adequacy. If the model is not adequate then the forecaster goes back to stage one and identify an alternative model, this is tested for adequacy and if adequate the forecaster proceeds to the final stage of the process. The fourth stage of the process is where the analyst uses the model chosen to forecast. This then ends the process.

3.14 The identification technique

The purpose of the identification phase is to choose a specific ARMA model from the general class of ARMA (p,q) models. The identification methods are rough procedures applied to the set of data to indicate the kind of representational model that will be further investigated. The aim here is to obtain some idea of the values of the p, d, q needed in the general linear ARIMA model and obtain initial estimates for the parameters. The task here is to identify an appropriate subclass of models from the general ARIMA family which may be used to represent the time series.

The first step is to determine whether or not the series is stationary. If the series is not stationary the series is differenced usually to the first or second degree to achieve stationarity. For the Box-Jenkins analysis the data must be made stationary and/or invertible. This reduces the process to a mixed ARMA process $\alpha(B)Z_t = \mu_0 + \theta(B)e_t$ where $Z_t = (1-B)^d Y_t = \nabla^d Y_t$

The next stage is to identify the resulting ARMA process. This is achieved by using the sample autocorrelation function and the sample partial autocorrelation function.

Apart from helping to guess the form of the model, they are used to obtain approximate estimates of the parameters of the model. These approximations are useful at the estimation stage to provide starting values for the iterative procedures employed at that stage.

3.15 Use of autocorrelation and partial autocorrelation function in identification.

For stationary mixed ARMA process of order (p, 0, q) $\alpha(B)Y_t = \theta(B)e_t$ the autocorrelation function satisfy the difference equation $\alpha(B)\rho_k = 0, k > q$ also if $\alpha(B) = \prod_{t-1}^{p}(1 - G_t B)$ the solution of this difference equation for the *k*th autocorrelation is, assuming distinct roots of the form $\rho_k = A_1 G_1^k + A_2 G_2^k + \ldots + A_p G_p^k, k > q - p$. The stationary requirement that the zeros of $\alpha(B)$ lie outside the unit circle implies that the roots, G_1, G_2, G_3,…,G_k lie inside the unit circle. Inspection of the equation $\rho_k = A_1 G_1^k + A_2 G_2^k + \ldots + A_p G_p^k, k > q - p$ shows that in the case of a stationary model in which none of the roots lie close to the boundary of the unit circle, the autocorrelation function will quickly die down or decay for moderate and large *k*. Suppose that a single real root, say G_1, approaches unity, so that $G_1 = 1 - \delta$, where δ is a small positive quantity. Then since for large *k*, $\rho_k = (1 - k\delta)$, the auto correlation function will not die out quickly and will fall off slowly and very nearly linearly. Similarly if more than one root approaches unity the autocorrelation function will decay slowly. Therefore if the autocorrelation function dies out slowly there is at least a root which approaches unity. As a result failure of the estimated autocorrelation to die out rapidly might logically suggest that the underlying stochastic process is non stationary in ∇Y_t, or some higher difference. It is therefore assumed that the degree of differencing, d, necessary to achieve stationarity has been reached when the autocorrelation function of $Z_t = \nabla^d Y_t$ dies out fairly quickly.

3.16 Identifying the Resultant Stationary ARMA Process.

J Jeffrey (1990), explained that if autocorrelations trails off exponentially to zero, an AR model is identified. Similarly if the partial autocorrelation trials off to zero then an MA model is indicated. If both autocorrelation and partial autocorrelation trails off to zero then a mixed ARMA model is indicated. Lastly the order of the AR model is indicated by the number of partial autocorrelation, and the order of the MA model by the number of autocorrelation that are statistically different from zero.

3.17 Estimation of the Parameters of the Model identified.

Once a model has been identified the next stage of the Box-Jenkins approach is to estimate the parameters of the model. ARIMA models can be fitted by least squares. An iterative non linear least square is applied to the parameter estimates of the ARMA (p, q) model. The method minimizes the sum of squares of errors, $\sum e_t^2$ as described earlier for the AR (p), MA (q) and ARMA (p, q).

Software programs are available for estimating most low order ARMA models and for testing parameters of the model. Jeffrey (1990), explained that, these programs permit us to asses the precision of the parameter estimates of what are called parsimonious forecasting models. Parsimonious have fewer rather than more parameters in the model. Since parsimony is a practical as well as a theoretical consideration, forecasters have found that simpler models are best. For this study the estimation of the parameters was done using MINITAB statistical software.

3.18 Testing the Model for Adequacy

After identifying an appropriate model for a time series data, it is very important to check that the model is adequate. This diagnostic checking is done by examining the error terms e_t to be sure that they are random. If the error terms are statistically different from zero, the model is not considered adequate. If several autocorrelations are large, we should return to the initial stage, select an alternative model, and then continue the analysis.

The test statistics used is the Ljung-Box chi-square statistic (denoted by Q). The Qstatistic where $Q = n(n+2)\sum_{i=1}^{k}\left(\frac{r_i^2}{n-k}\right)$ is approximate distributed as a χ^2 with $(k - p - q)$ degrees of freedom. Where n is the length of the time series, k is the first k autocorrelation being checked, p is the order of the AR process, q is the order of the MA process and r_i, is the estimated autocorrelation coefficient of the ith residual term. If the calculated value of Q is greater than χ^2 with $(k - p - q)$ degrees of freedom the model is considered inadequate. The forecaster should then return to selecting an alternative and continue with the Box-Jenkins model until satisfactory model is found.

Finally if two or more models are judged to be about equal although no model is an exact fit, the principle of parsimony should prevail.

3.19 Forecasting.

The last stage of the Box –Jenkins approach is to forecast with the model selected. Jeffrey (1990) explained that ARIMA models are particularly suitable for short term forecasting, that is, where the lead time n is not much longer than (p + q.)

As new observations for a time series are obtained, the model should be re-examined and checked for accuracy. If the time series seems to be changing over time the parameters for the model should be recalculated or an entirely new model may have to be developed. When small differences in forecast errors are observed, we should only recalculate the model parameters. However, if large differences are observed in the size of the forecast error, this would indicate the need for a new forecasting model. At this time, we should return to the first stage of the Box-Jenkins process.

3.20. DATA ON GHANA'S INFLATION

Table 4.6 under appendix A shows the data of Ghana's monthly inflation rates from January 1990 to December 2010, totalling two hundred and fifty two (252) monthly observations. The data was obtained from the Statistical Service Department of Ghana. Figures 3.1 and 3.2 show the plot of Ghana's monthly inflation. and the trend analysis plot respectively. Figures 3.3 and 3.4 also describe the features of the data. That is the autocorrelation plot and the partial autocorrelation plot respectively.

Figure 3.1 TIME SERIES PLOT OF GHANA'S MONTHLY INFLATION

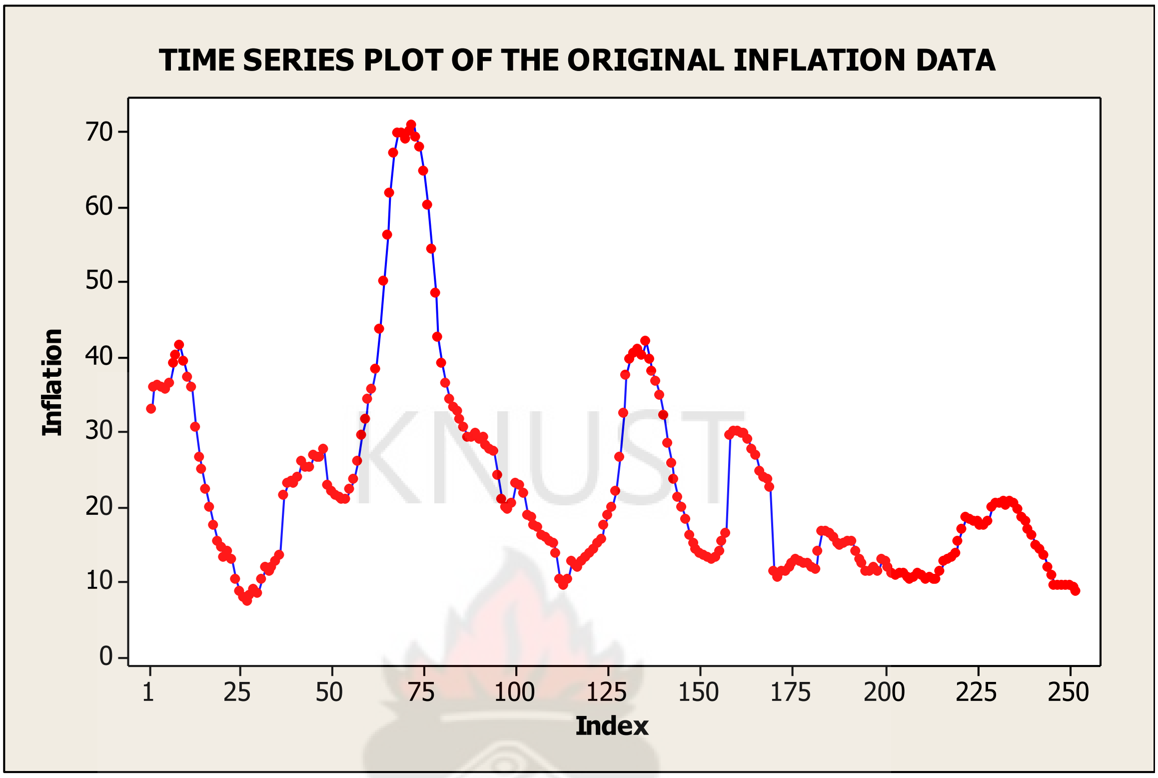


Figure 3.2 TREND ANALYSIS PLOT OF GHANA'S MONTHLY INFLATION

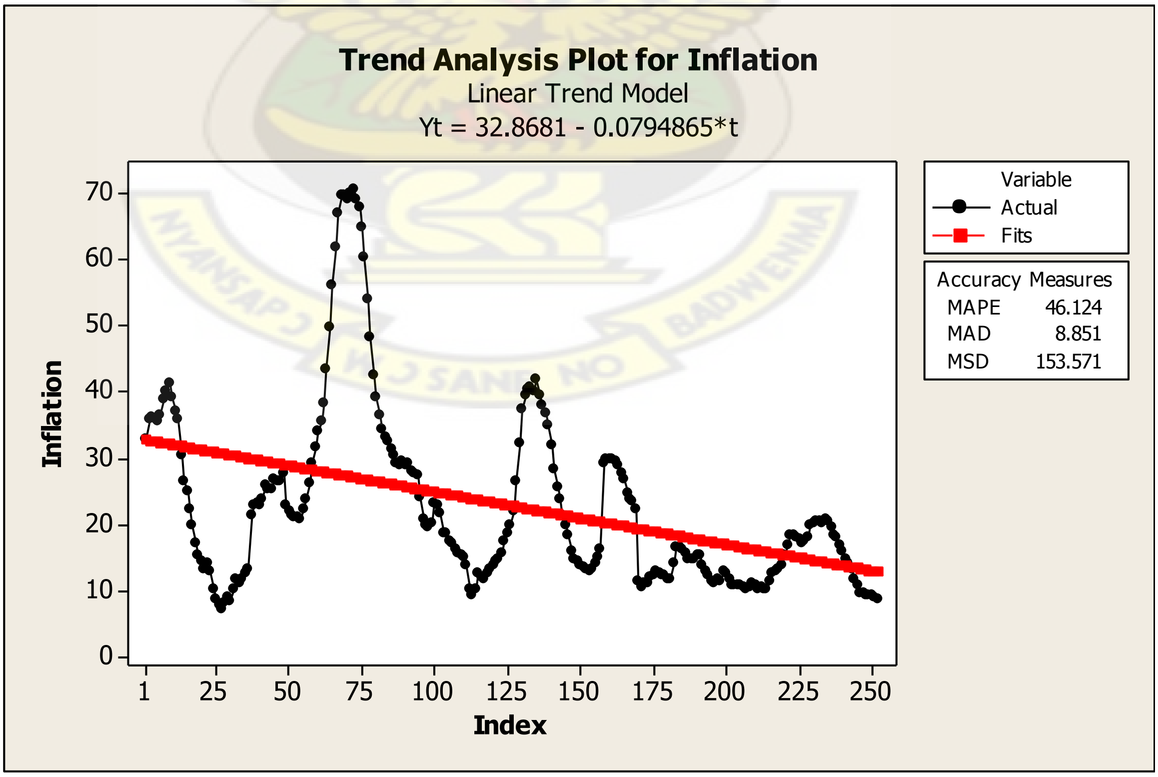


Figure 3.3 AUTOCORRELATION PLOT OF GHANA'S INFLATION

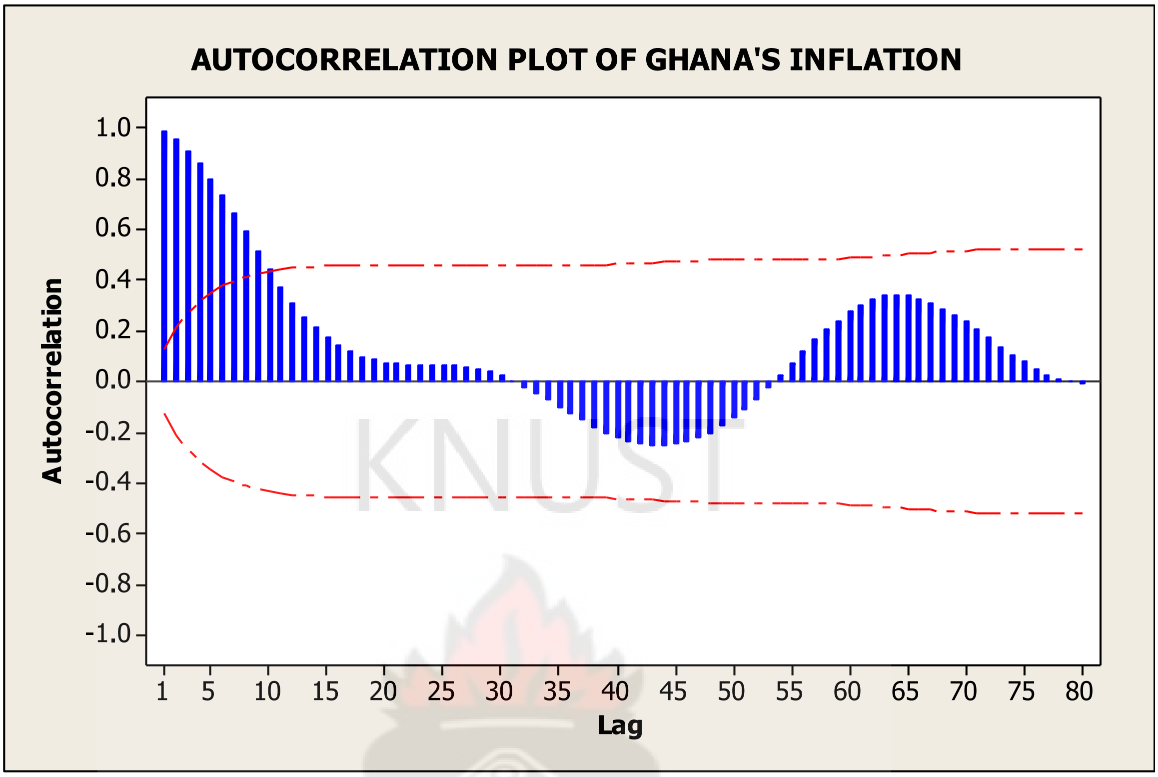
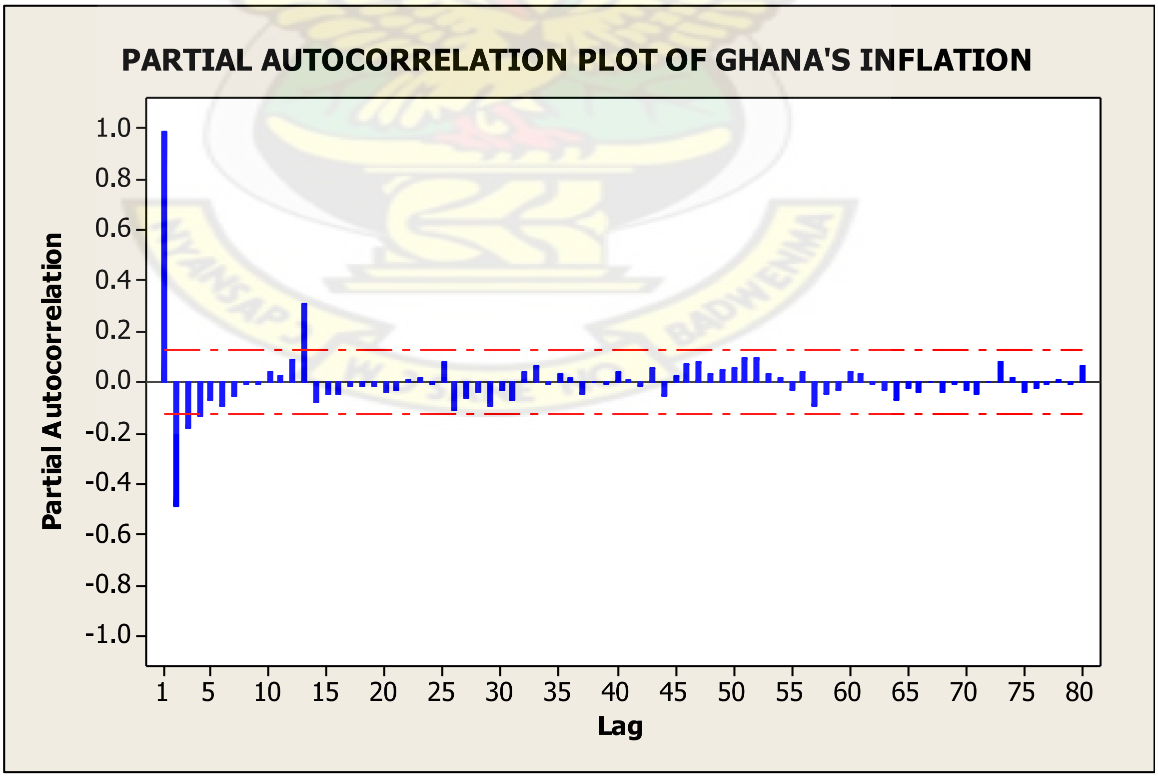


Figure 3.4 PARTIAL AUTOCORRELATION PLOT OF GHANA'S INFLATION



A look at the time series plot of the original data that is Figure 3.1 suggests that the series is non-stationary. Furthermore the trend analysis as shown in Figure 3.2 shows a decreasing trend. However, the ACF plot as shown in Figure 3.3 dies down in a sinewave fashion and the PACF plot as shown in Figure 3.4 tails of at lag 2 (though there is a spike at lag 13 it is considered spurious and therefore neglected).Therefore an AR (2) model is suspected. The result of estimates of parameters, the ACF and the PACF of the residuals obtained by MINITAB are shown in tables 3.5(a) and 3.5(b),Figures 3.6 and 3.7 respectively..

Table 3.5(a) ESTIMATES OF PARAMETERS FOR AR(2) MODEL

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
AR 1	1.5790	0.0510	30.96	0.000
AR 2	−0.5986	0.0511	−11.72	0.000
Constant	0.4347	0.1121	3.88	0.000
Mean	22.140	5.711		

Number of observations: 252

Residuals: SS = 784.962 (back forecasts excluded)

MS = 3.152, DF = 249

Table 3.5(b) Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Modified Box-Pierce (Ljung-Box) Chi-Square statistic				
Lag	12	24	36	48
Chi − Square	59.1	66.2	79.8	97.9
DF	9	21	33	45
P − Value	0.000	0.000	0.000	0.000

Figure 3.6 ACF PLOT OF RESIDUALS OF GHANA'S INFLATION

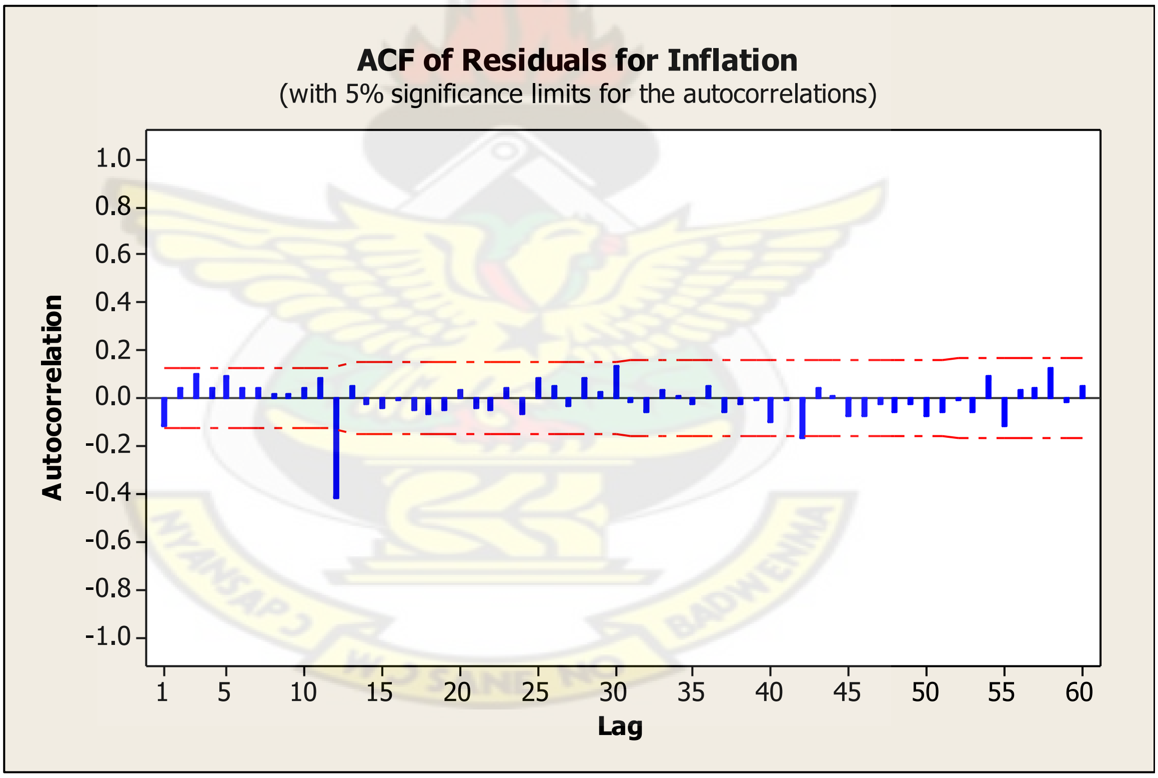


Figure 3.7 PACF OF RESIDUALS OF GHANA'S INFLATION

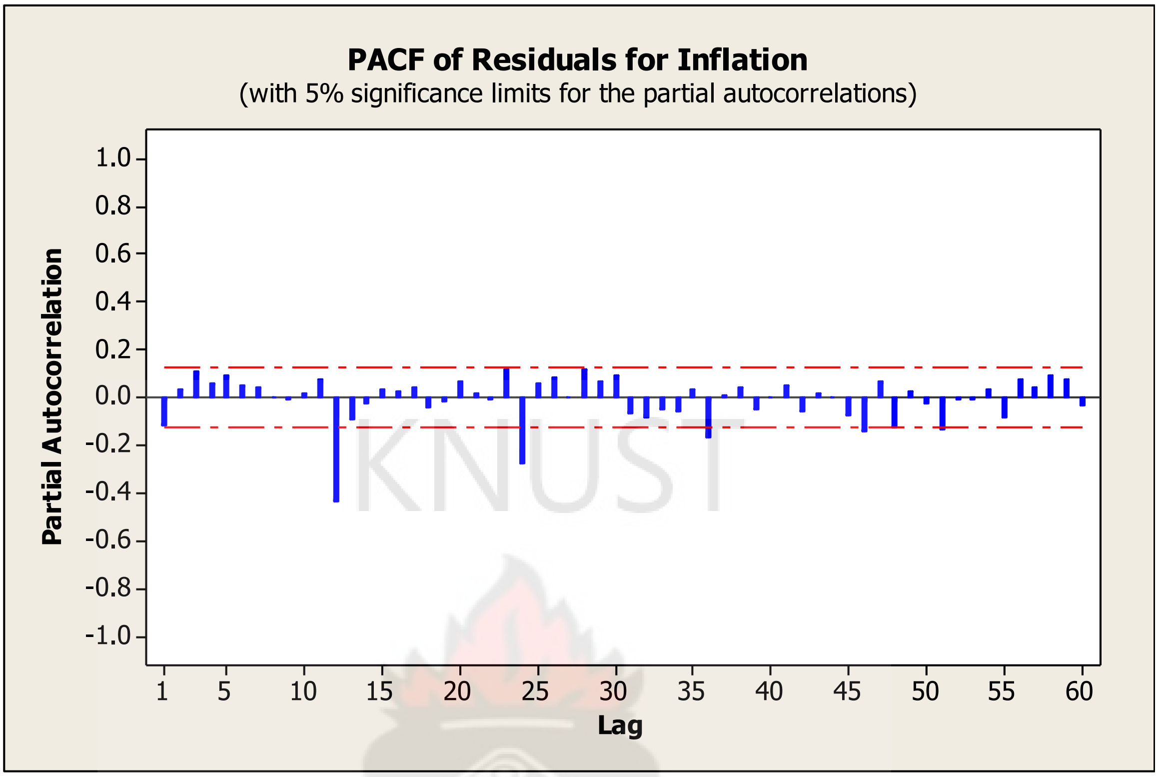
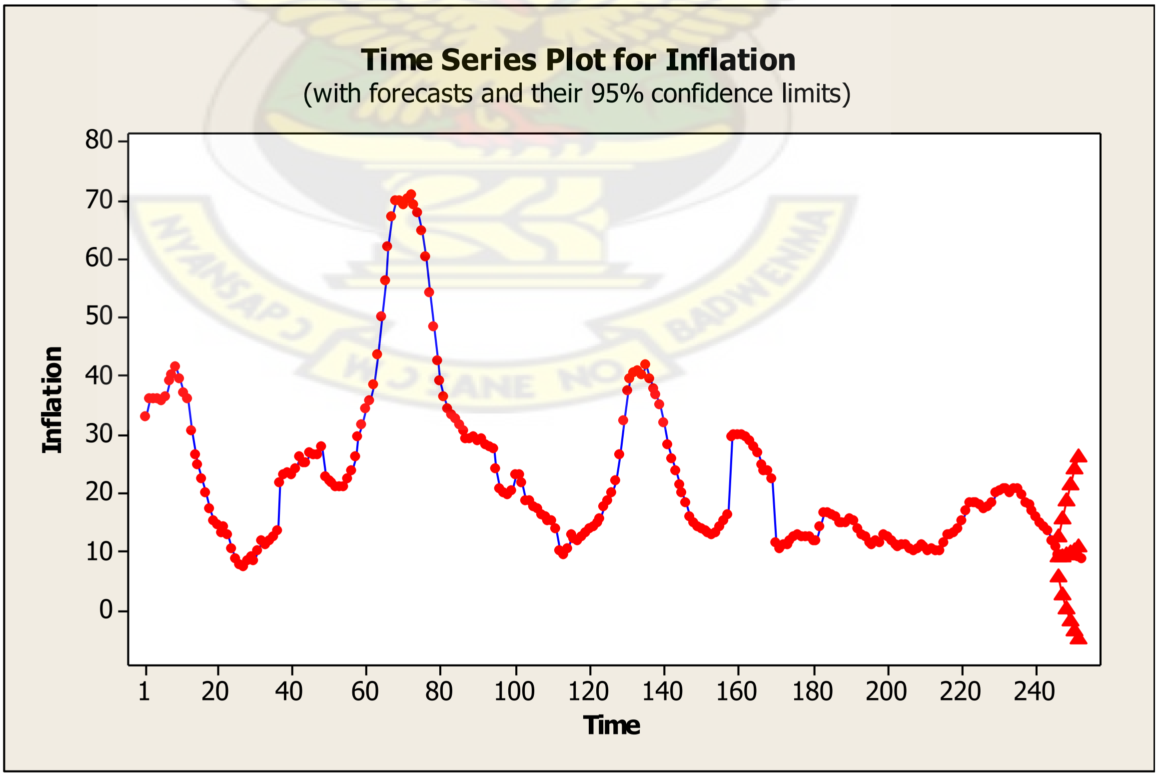


Figure 3. 8 TIME SERIES PLOT FOR FORECAST USING AR(2)



A look at figures 3.6 and 3.7 show some significant number of spikes outside the limit $-2\sigma_{\phi kk} \leq \phi_{kk} \leq 2\sigma_{\phi kk}$ i.e $\frac{-2}{\sqrt{252}} \leq \phi_{kk} \leq \frac{2}{\sqrt{252}}$ which equals $-0.126 \leq \phi_{kk} \leq 0.126$ suggesting that the residuals are not random. Figure 3.5 also shows that the P-values for the Ljung-Box statistics are not significant. The forecast as shown by figure 3.8 do not seem to be consistent with the forecast of inflation figures. We try differencing the data to bring about stationarity in mean.

Figure 3. 9 TIME SERIES PLOT OF 1ST DIFF. OF THE ORIGINAL DATA

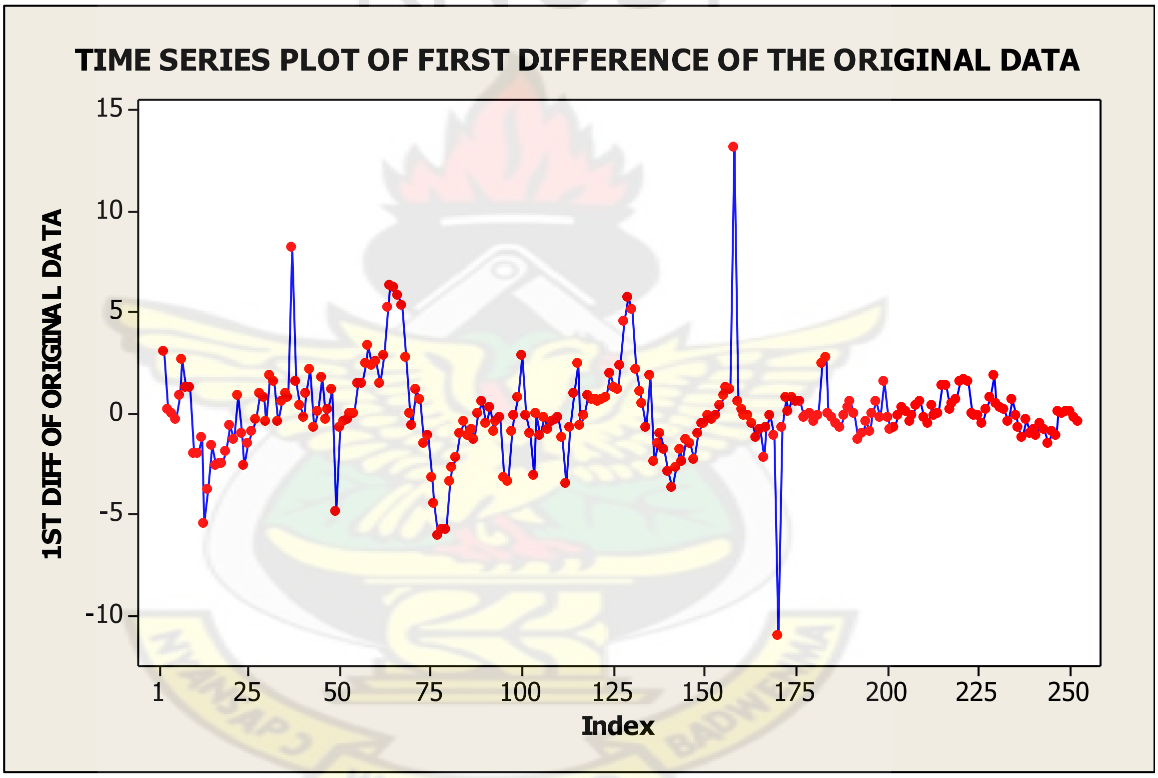


Figure 3.9 shows the time series plot of the first difference of Ghana's original inflation data. There is stationarity in mean and the existence of seasonality is evident.

Figure 3. 10 TREND ANALYSIS FOR 1ST DIFF. OF THE ORIGINAL DATA

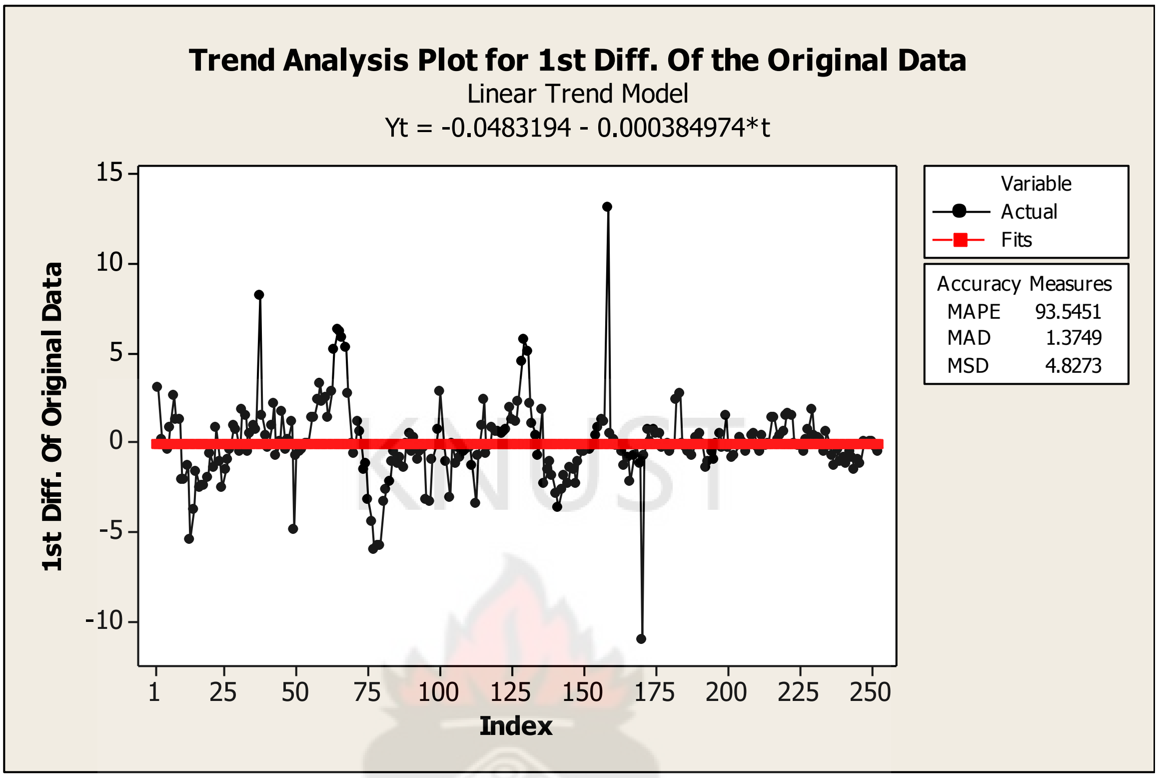


Figure 3. 11 ACF OF 1ST DIFF. OF THE ORIGINAL DATA

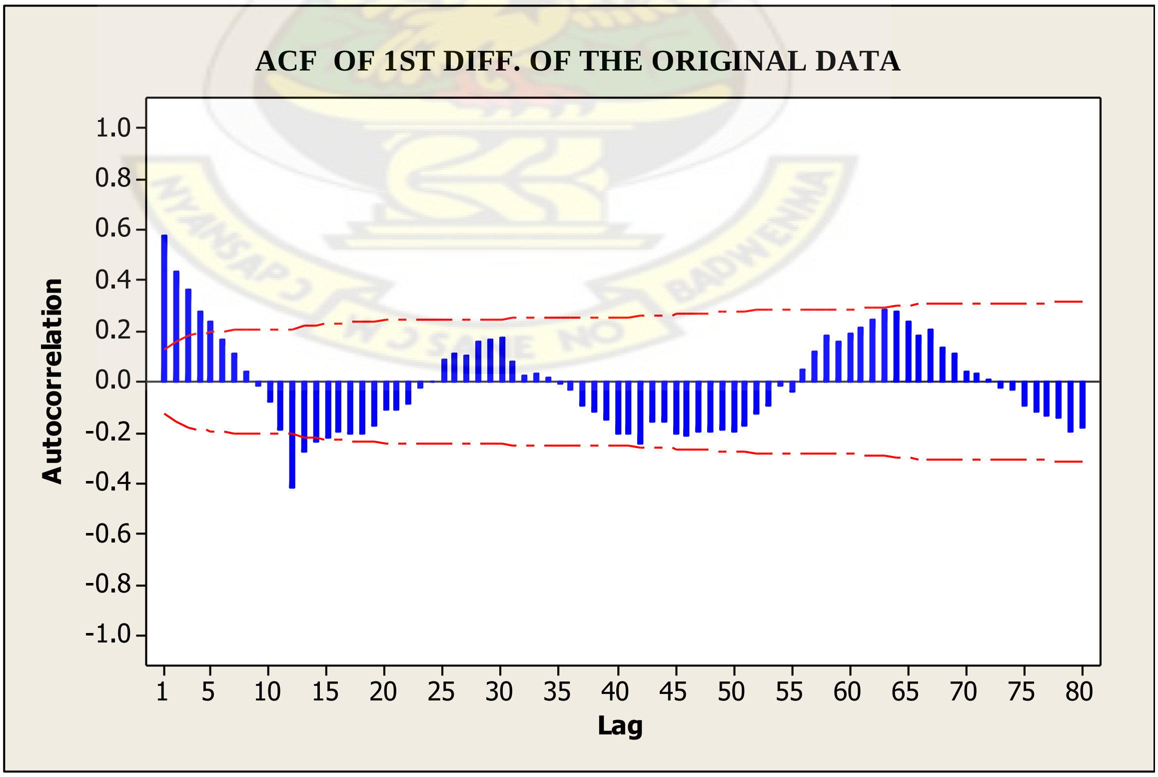
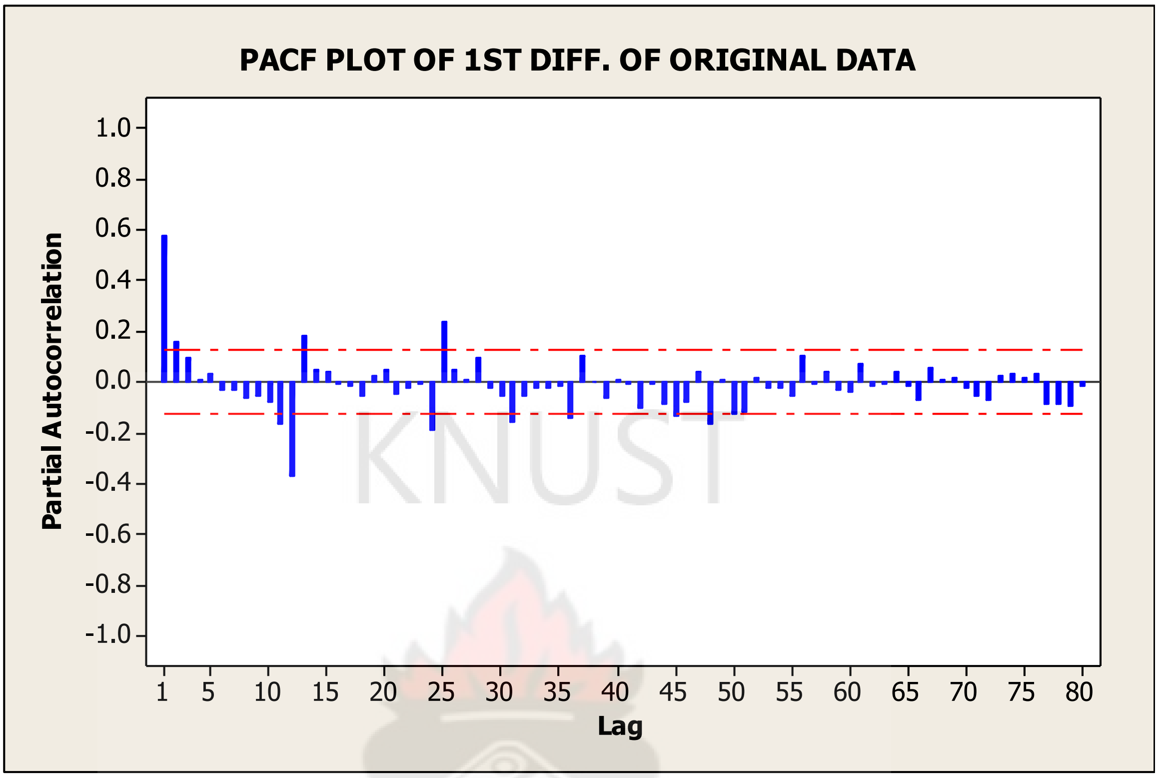


Figure 3.12 PACF OF 1ST DIFF. OF THE ORIGINAL DATA



Figures 3.11 and 3.12 show the autocorrelation function and the partial autocorrelation function of the first difference of Ghana's original inflation data respectively. The ACF dies in a sinewave form and the PACF also shows significant number of spikes dieing down in a sinewave fashion.

Figure 3.13 TIME SERIES PLOT OF THE SEASONAL DIFF. OF THE 1ST DIFF. DATA

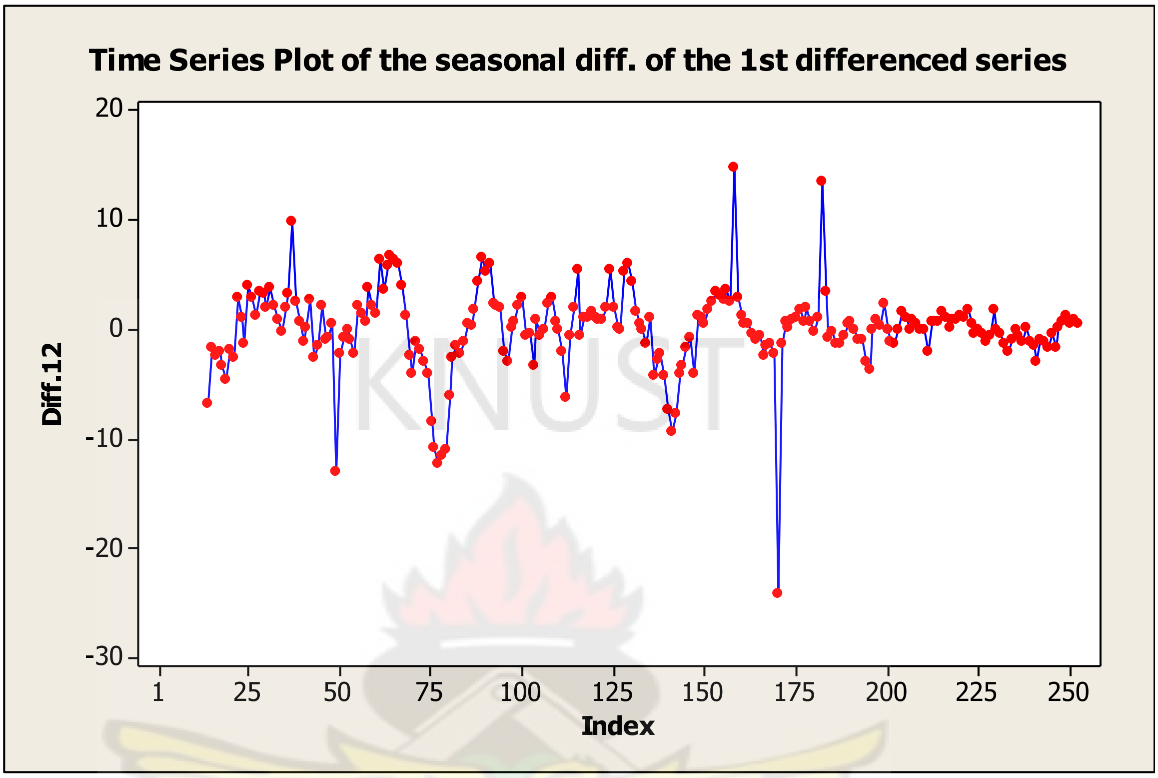


Figure 3.13 shows the time series plot of the seasonal difference of the first differenced of Ghana's inflation data which shows stability in mean at both the seasonal and the nonseasonal levels.

Figure 3.14 TREND ANALYSIS OF THE SEASONAL DIFF. OF THE 1ST DIFF. DATA

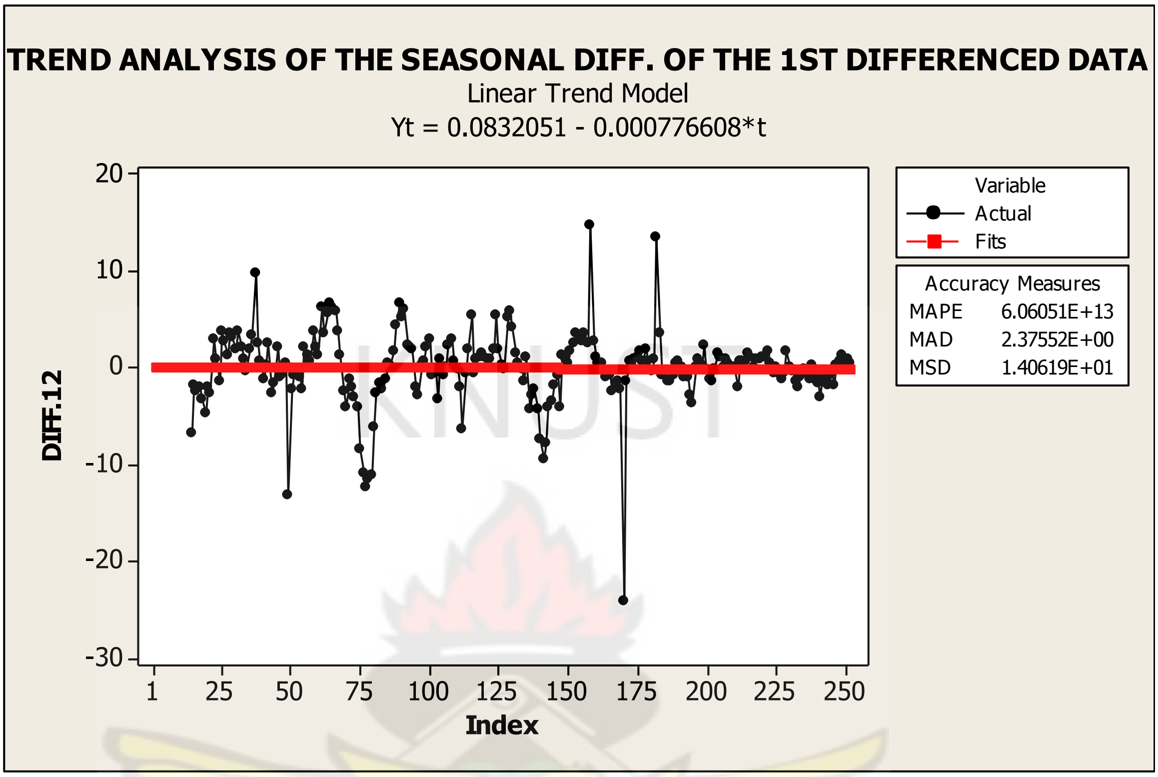


Figure 3.14 shows the trend analysis of the seasonal difference of the first differenced of Ghana's original inflation data. The trend is neither increasing nor decreasing which is indicative of stationarity in mean.

Figure 3.15 ACF OF THE SEASONAL DIFF. OF THE 1ST DIFFERENCED DATA

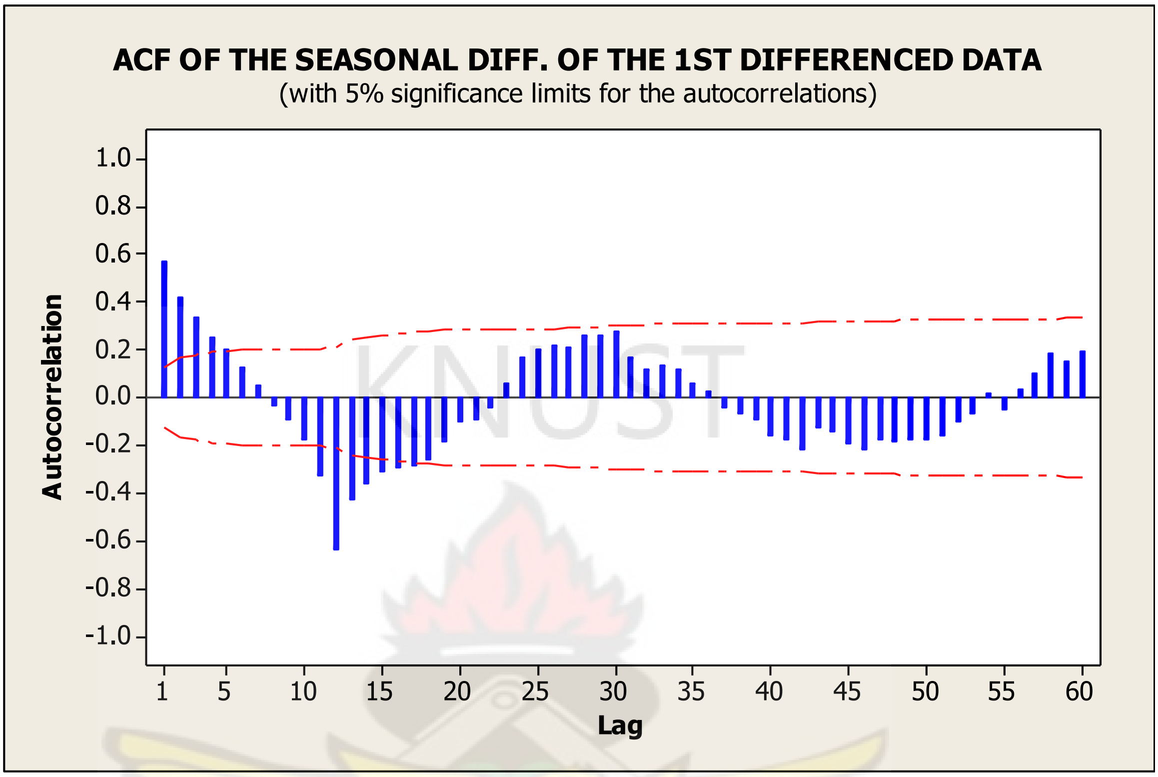
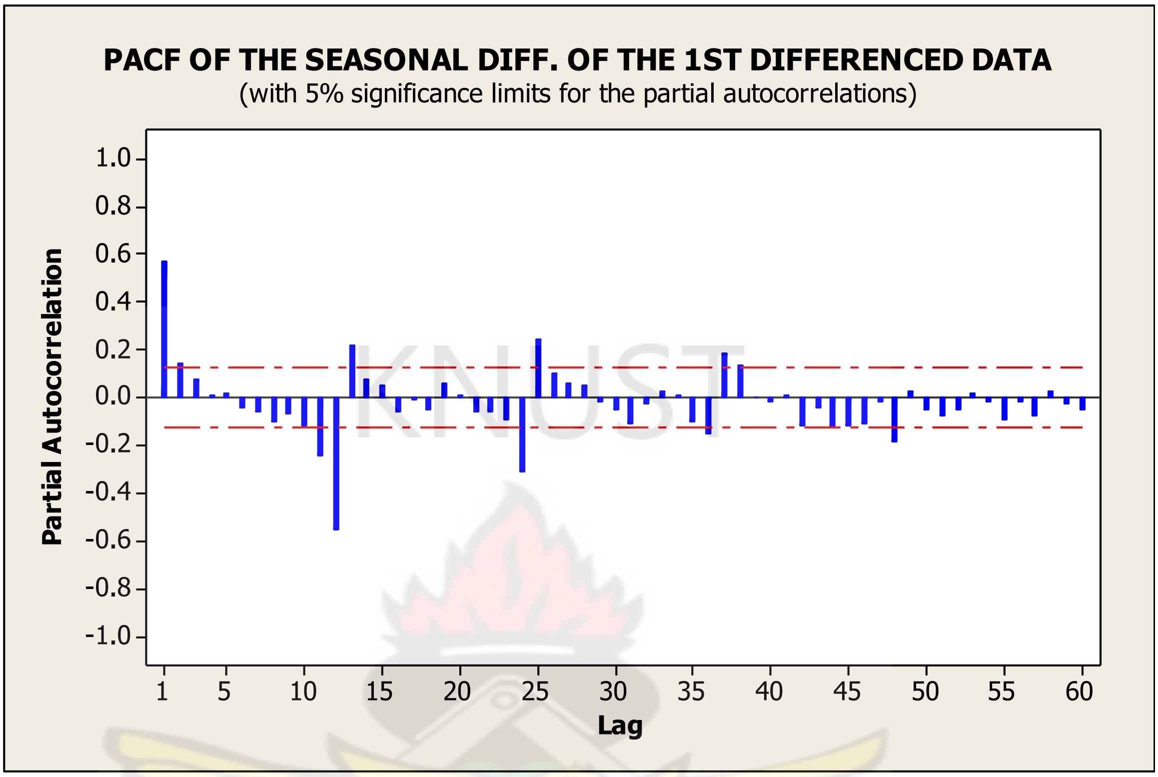


Figure 3.15 shows the autocorrelation function of the seasonal difference of the first differenced of Ghana's original inflation data moving in a sinewave fashion.

Figure 3.16 PACF OF THE SEASONAL DIFF. OF THE 1ST DIFFERENCED DATA



The time series plot of the 1st differenced data and the trend analysis as shown in figures 3.9 and 3.10 show stationarity in mean and variance. There were significant spikes in the time series plot at lags 13, 25, 37, 49 etc. This is indicating that seasonality is evident in the monthly inflation rates with a period of 12.This call for seasonal differencing of the 1st non-seasonal differenced data. as shown in figure 3.13. Figures 3.11 and 3.12 are the plots of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the 1st differenced data. The ACF dies down after lag1 and the PACF also tails off after lag1, suggesting that p=1 and q =1 would be needed to describe these data as coming from a non-seasonal autoregressive and a moving average process respectively. So the time series model that give rise to these observations was an ARIMA (1, 1, 1) model, since the data was differenced once (i.e. d =1) to attain stationarity.

Figures 3.13 and 3.14 show the time series plot of the seasonal difference of the 1st differenced series and the trend analysis plot respectively. The trend analysis shows stationarity at the seasonal level. Figures 3.15 and 3.16 show the ACF and the PACF of the seasonal difference of the 1st differenced series .respectively. A critical look at the seasonal lags show that both ACF and the PACF spikes at seasonal lag 12 dies down to zero for other seasonal lags. Suggesting that P =1 and Q=1 would be needed to describe these data as coming from a seasonal autoregressive and moving average process. So the time series model that give rise to these observation was an ARIMA(1,0,1).Hence ARIMA(1,1,1)$(1,0,1)^{12}$could be the suggested model for the series at both the non-seasonal and the seasonal levels. With these suggestions the appropriate model is selected in the next chapter.

CHAPTER 4

DATA ANALYSIS AND RESULTS

4.1 Identification of the ARIMA model.

Two goodness-of-fit statistics that are most commonly used for model selection are, Akaike information criterion (AIC) and Schwarz Bayesian information criterion (BIC). The AIC and BIC are determined based on a likelihood function. The AIC and BIC are calculated using the formulas below: $AIC = \ln(SSE) + \frac{2k}{n}$ and $BIC = \ln(SSE) + \frac{k}{n}\ln(n)$ where n is the total number of observations, SSE is the sum of the squared errors, and $k = (p + q + P + Q + d + sD)$ Here n = 252 data points. Four tentative ARIMA models are tested for the data series and the corresponding AIC and BIC values for the models are shown in Table 4.1. The objective here is to select models that provide the minimum AIC and BIC values.

Table 4.1 AIC and BIC values for four Tentative SARIMA Models

ARIMA MODEL(p,d,q)	AIC	BIC
(1 1 1)(1 0 1)12	**6.2469**	**6.3907**
(1 1 1)(0 0 1) 12	**6.2395**	**6.3473**
$(1\ 1\ 1)(1\ 0\ 0)^{12}$	6.4373	6.5451
$(0\ 1\ 1)(1\ 0\ 1)^{12}$	6.4116	6.5195

The models that have the lowest AIC and BIC are ARIMA $(1,1,1)(0,0,1)^{12}$ and ARIMA $(1,1,1)(1,0,1)^{12}$. Since two models are identified, the most suitable model is selected by the principle of parsimony.ARIMA $(1, 1, 1)(0, 0, 1)^{12}$ model has fewer parameters than ARIMA $(1, 1, 1)(1, 0, 1)^{12}$ model. Furthermore all the coefficients of ARIMA $(1, 1, 1)(0,0,1)^{12}$model are significantly different from zero and the estimated values satisfy the stability as shown in table 4.3. However, the SAR (12) parameter for $ARIMA(1,1,1)(1,0,1)^{12}$ model is not significant as shown in table 4.2. Hence after removing the $SAR(12)$ term from the model, it then reduce to $ARIMA(1,1,1)(0,0,1)^{12}$ model. We then proceed to the next stage of the Box-Jenkins approach which is the estimation of parameters of the tentative model.

4.2 Parameter Estimation of SARIMA$(1,1,1)(1,0,1)12$ and SARIMA$(1,1,1)(0,0,1)^{12}$models

Once a suitable **SARIMA**$(\mathbf{p},\mathbf{d},\mathbf{q})(\mathbf{P},\mathbf{D},\mathbf{Q})^{12}$ structure is identified, the second step is the parameter estimation or fitting stage. The parameters are estimated by the maximum likelihood method. The results of parameter estimations are reported in tables 4.2 and 4.3.

Table 4.2(a) Estimates of parameters of SARIMA $(1,1,1)(1,0,1)12$

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
AR 1	0.7944	0.0605	13.13	0.000
SAR 12	0.0192	0.0861	0.22	0.824
MA 1	0.3177	0.0945	3.36	0.001
SMA 12	0.7545	0.0580	13.01	0.000

Differencing: 1 regular difference

Number of observations: Original series 252, after

Differencing 251

Residuals: SS = 500.276 (back forecasts excluded)

MS = 2.025   DF = 247

Table 4.2(b) Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Modified Box-Pierce (Ljung-Box) Chi-Square statistic				
Lag	12	24	36	48
Chi-Square	4.1	13.1	24.1	32.9
DF	8	20	32	44
P-Value	0.848	0.874	0.839	0.891

Table 4.3(a) Estimates of parameters of the tentative SARIMA $(1,1,1)(0,0,1)12$ model

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
AR 1	0.7958	0.0597	13.33	0.000
MA 1	0.3189	0.0939	3.40	0.001
SMA 12	0.7446	0.0430	17.31	0.000

Differencing: 1 regular difference

Number of observations: Original series 252,

After differencing 251

Residuals: SS = 500.534 (back forecasts excluded)

MS = 2.018, DF = 248

Table 4.3(b) Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Modified Box-Pierce (Ljung-Box) Chi-Square statistic				
Lag	**12**	**24**	**36**	**48**
Chi-Square	4.3	13.3	24.4	33.1
DF	9	21	33	45
P-Value	0.893	0.898	0.862	0.906

We proceed in our analysis to check if the parameters contained in the models are significant. This ensures that there are no extra parameters present in the model and the parameters used in the model have significant contribution, which can provide the best forecast. The estimates of autoregressive, moving average and the seasonal moving average parameters are labelled "AR..1", "MA..1" and "SMA..12", which are 0.7958, 0.3189 and 0.7446, respectively. Based on 95% confidence level we conclude that all the coefficients of the ARIMA $(1, 1, 1)(0,0,1)^{12}$ model are significantly different from zero as shown on table 4.3(a). Furthermore the p-values for the Ljung-Box statistic clearly all exceed 5% for all lag orders, indicating that there is no significant departure from white noise for the residuals. We then proceed to the next step after parameter estimation which is the Diagnostic Checking or model validation. The Box and Jenkins (1970) estimation process for seasonal ARIMA model is shown in Figure 4.2.

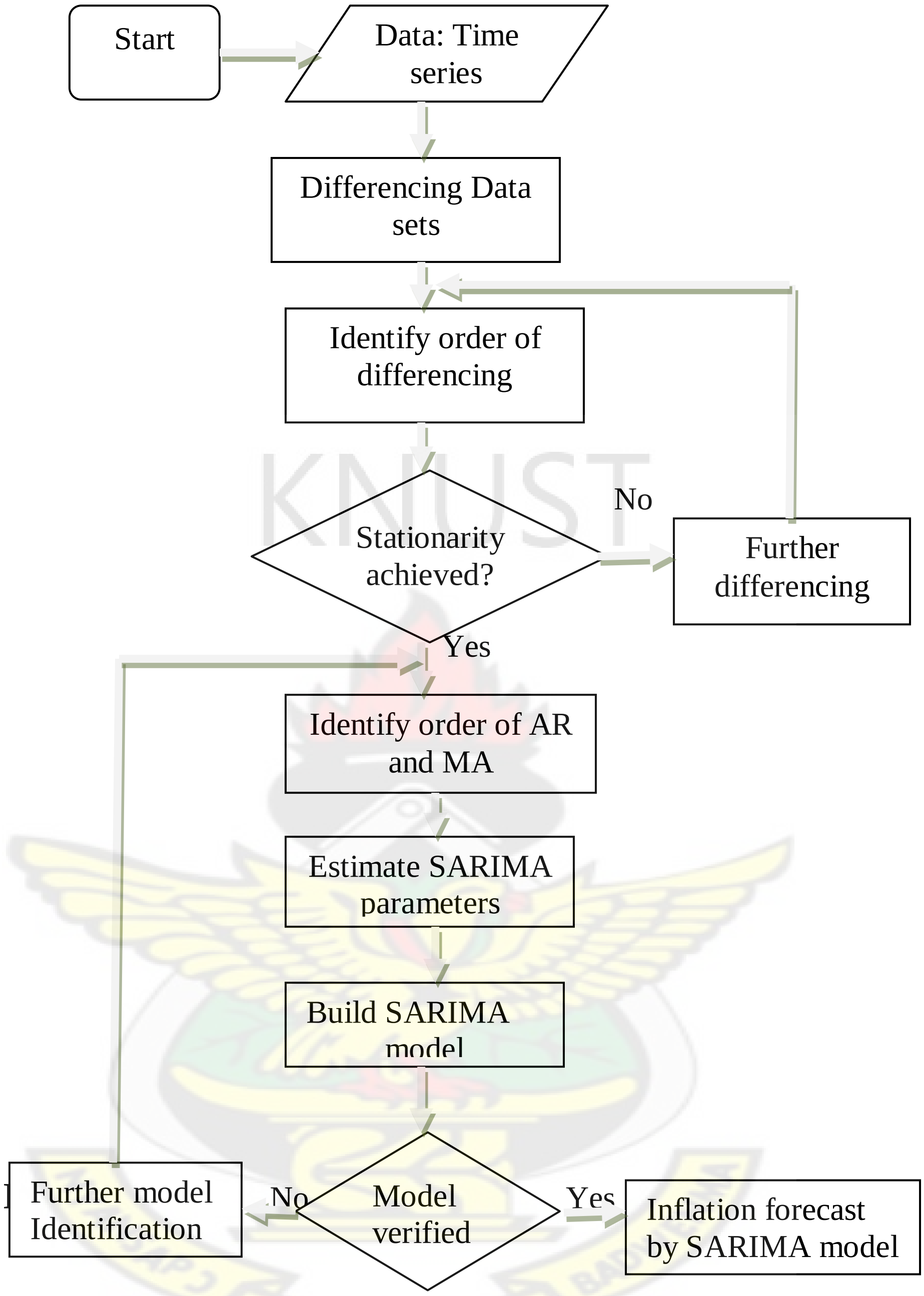
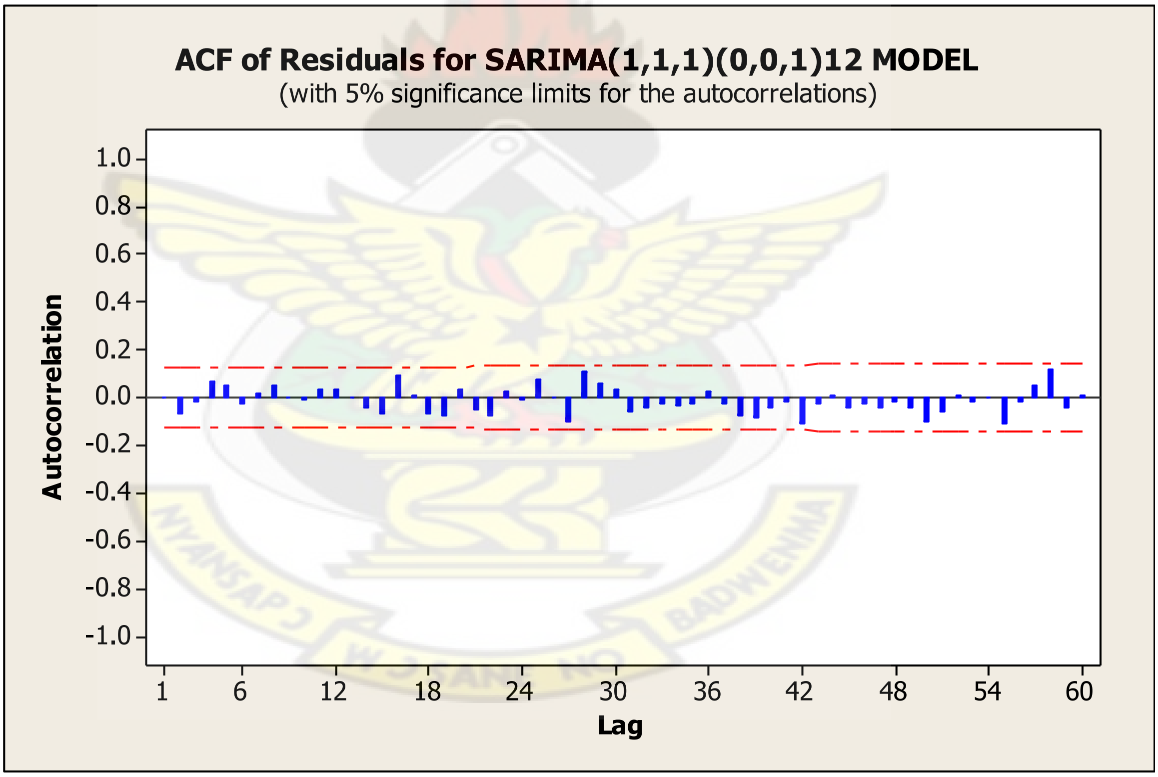


Figure 4.2: Flow chart for SARIMA estimation process

4.3 Diagnostic Checking and Model Validation

The model verification is concerned with checking the residuals of the model to determine if the model contains any systematic pattern which can be removed to improve on the selected ARIMA model. Although the selected model may appear to be the best among a number of models considered, it is also necessary to do diagnostic checking to verify that the model is adequate. Verification of an ARIMA model is tested (i) by verifying the ACF of the residuals,(ii) by verifying the normal probability plot of the residuals.

Figure 4.3 ACF of Residuals for SARIMA (1,1,1)(0,0,1)^{12} Model



From Figure 4.2, the autocorrelation checks of the residuals indicate that the model is good because they follow a white noise process. That is the residuals have zero mean, constant variance and also uncorrelated. Also the p-values for the Ljung-Box statistic from table 4.3 as shown clearly exceed 5% for all lag orders, indicating that there is no significant departure from white noise for the residuals. Since the model diagnostic tests show that all the parameter estimates are significant and the residual series are random, it can be concluded that SARIMA (1, 1, 1)(0, 0, 1)$_{12}$ models is adequate for the inflation series. Therefore SARIMA (1,1,1)(0,0,1)$_{12}$ is used to forecast the inflation series of Ghana.

4.4 Point forecast with SARIMA $(1,1,1)(0,0,1)12$ model.

The ARIMA(1,1,1)(0,0,1)$_{12}$ is selected to forecast the inflation variable, where autoregressive term p = 1(non-seasonal),P=0(seasonal) [that is ,(1-αB)(1-0)]; differencing term d =1(non-seasonal difference), Q=0(seasonal difference)[that is ,(1-B)(1-0)] and moving average term q =1(non-seasonal), Q = 1(seasonal) [that is, (1-$\theta_1 B$)(1-$\theta_{12}B^{12}$)] . For the dataset in Table 3.1, the fitted model is given by

$$(1-B)(1-\alpha B)y_t = (1-\theta_1 B)(1-\theta_{12}B^{12})e_t \tag{4.1}$$

$$y_t - \alpha B y_t - B y_t + \alpha B^2 y_t = e_t - \theta_{12}B^{12}e_t - \theta_1 B e_t + \theta_1\theta_{12}B^{13}e_t$$

$$y_t = e_t - \theta_{12}B^{12}e_t - \theta_1 B e_t + \theta_1\theta_{12}B^{13}e_t + \alpha B y_t + B y_t - \alpha B^2 y_t \tag{4.2}$$

Transforming the back operator, equation (4.2) becomes;

$$y_t = e_t - \theta_{12}e_{t-12} - \theta_1 e_{t-1} + \theta_1\theta_{12}e_{t-13} + (1+\alpha)y_{t-1} - \alpha y_{t-2} \tag{4.3}$$

4.5. Forecast Results by SARIMA $(1,1,1)(0,0,1)12$ model

In order to forecast one period ahead that is,y_{t+1}, the subscript of the equation(4.3) is increased by one unit throughout as given by;

$$y_{t+1} = (1+\alpha)y_t - \alpha y_{t-1} + e_{t+1} - \theta_{12}e_{t-11} - \theta_1 e_t + \theta_1\theta_{12}e_{t-12} \tag{4.4}$$

The term e_{t+1} is not known because the expected value of future random errors has been taken as zero. There are 252 data points from January 1990 to December 2010 used to build the ARIMA model. From table 4.3, using $\alpha = 0.7958$, $\theta_1 = 0.3189$, $\theta_{12} = 0.7446$, $\therefore$ $\theta_1\theta_{12} = 0.237453$.Equation (4.4) is given as;

$$y_{t+1} = 1.7958y_t - 0.7958y_{t-1} - 0.7446e_{t-11} + 0.237453e_{t-12} - 0.3189e_t \quad (4.4)$$

In order to forecast inflation for the period 253(that is, January 2011), equation (4.4) is given by

$$\hat{y}_{253} = 1.7958y_{252} - 0.7958y_{251} - 0.7446\hat{e}_{241} + 0.237453\hat{e}_{240} - 0.3189\hat{e}_{252} + \hat{e}_{253}$$

$$\hat{e}_{253} = 0, \hat{e}_{240} = y_{240} - \hat{y}_{240} = 16.0 - 15.6086 = 0.3914$$

$$\hat{e}_{241} = y_{241} - \hat{y}_{241} = 14.8 - 14.9226 = -0.1226$$

$$\hat{e}_{252} = y_{252} - \hat{y}_{252} = 8.6 - 8.6612 = -0.0612, y_{252} = 8.6, y_{251} = 9.1$$

The forecast quantity for period 253 can be calculated as follows:

$$\hat{y}_{253} = 1.7958(8.6) - 0.7958(9.1) - 0.7446(-0.1226) + 0.237453(0.3914) - 0.3189(-0.0612) + 0$$

$$= 8.41\%$$

Once our model has been found and its parameters have been estimated, we can use it to make our prediction. Table 4.4 summarizes 12 months ahead inflation forecast for the year 2011, starting from January to December 2011 along side the existing actual values from January to March 2011. with 95% confidence interval.

Comparing the predicted rates from January to March with the actual rates, we can see that the predicted values are close to the actual values. Also, all the actual values fall inside the confidence interval. Hence, we say that, ARIMA (1, 1, 1) $(0, 0, 1)_{12}$ model is adequate to be used to forecast monthly inflation rate in Ghana.

Table 4.4. 12- Months Forecasted Inflation for 2011(January-December)

			95 Percent Limits		
Month	Period	Forecast (%)	Lower	Upper	Actual (%)
January	253	8.4059	5.6208	11.1909	9.10
February	254	8.2471	3.2796	13.2146	9.16
March	255	8.2081	1.0381	15.3781	9.13
April	256	8.4941	-0.8625	17.8508	9.02
May	257	8.5709	-2.9262	20.0679	8.90
June	258	8.6232	-4.9495	22.1959	8.59
July	259	8.6486	-6.9254	24.2227	N/A
August	260	9.2634	-8.2337	26.7605	N/A
September	261	10.3801	-8.9616	29.7218	N/A
October	262	11.0682	-10.0416	32.1780	N/A
November	263	11.5643	-11.2403	34.3689	N/A
December	264	12.0151	-12.4150	36.4451	N/A

Table 4.5: Basic statistic of Ghana's monthly inflation data in percentages

No.of observations	Mean	St.Dev.	Variance	Min.	Max.
252	22.813	13.702	187.751	7.3	70.8

CHAPTER 5

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 SUMMARY OF RESULTS

Table 4.5 shows basic statistic of Ghana’s monthly inflation for the past two decades. We set out by analysing Ghana’s monthly inflation from 1990 to 2010 that is 252 data points were analysed with a mean inflation of 22.8%, standard deviation of 13.7%, and variance of 187.8%. Minimum and maximum inflation for the past 21 years are 7.3% and 70.8% respectively.

From figure 3.1, it can be confirm that inflation exhibit volatility starting from somewhere around 1993. The volatility in Ghana’s inflation series can be attributed to several economic factors. Some of these factors are money supply, exchange rate depreciation, petroleum price increases, and poor agricultural production. For instance, inflation rate increased from 13.30% in December 1992 to 21.50% in January 1993.The rate fluctuated between 21.50% and 26.20% throughout the 1993 This increase can be attributed to to an increase in petroleum prices on the world market. Between 1994 and 1995, there was a sharp increase in inflation rate from 22.80% in January 1994 to 70.80% in December 1995.This sharp increase can be attributed to several factors such as increase in petroleum prices from 1993 to 1995., the depreciation of the Ghanaian cedi at the exchange rate level relative to the same years and poor performance of the agriculture sector in 1995.When the agricultural productivity started improving, between January 1996 and May 1999, inflation rate dropped from 69.20% to 9.40%. From June 1999 to March 2001, the rate of inflation rose again from 10.30% to 41.90%.This sudden rise of inflation could be attributed to an increase world oil price and a decrease in world market cocoa prices as well as reduction in agricultural performance in the year 2000. From the year 2002 to 2009, the inflation rate fluctuated between 9.50% and 30.30%. Most of these fluctuations were as a result of increase in petroleum prices.

In the year 2007, Ghana adopted a monetary policy called Inflation Targeting. It is a money policy in which the central bank target inflation rate and then attempt to direct actual inflation rate towards the target through the use of other monetary policies. A lot of countries worldwide are practising this policy and it has helped others improved upon their economy. The target set by the central bank is to bring inflation to a single digit. The single digit inflation rate has not been realised since the adaptation of the Inflation Targeting policy. From January 2007 up to July 2009, the rate is between 10.90% to 20.50%. The inflation rate then dropped consistently from 20.50% in July 2009 to a figure of 8.60% in December 2010.Since 1992 till date the scramble to reduce inflation to a single digit by successive government has not been successful.

Box-Jenkins Seasonal Autoregressive Integrated Moving Average (SARIMA) was employed to analyse monthly inflation rate of Ghana from January 1990 to December 2010. The study mainly intended to forecast the monthly inflation rate for the coming period of January, 2011 to December 2011.

Series of tentative models were developed to forecast Ghana's monthly inflation. But based on minimum AIC and BIC values and after the estimation of parameters and series of diagnostic test were performed, ARIMA$(1,1,1)(0,0,1)_{12}$ model was judge to be the best model for forecasting after satisfying all model assumptions.

The forecast results revealed a decreasing pattern of inflation rate in the first quarter of the forecasted period and turning point at the beginning of the second quarter of the forecasted period, where the rates takes an increasing trend till the end of the forecast period.

5.2 CONCLUSIONS

Our forecast results also brought to bear two significant points. Firstly, the forecast values from the beginning of the first quarter of 2011 up to the beginning of the third quarter of 2011 has been within the threshold of what the Bank of Ghana has targeted, namely 8.6%. Secondly, at the beginning of the third quarter we see high inflation rearing its ugly head. That is the single digit inflation which the country is experiencing currently may change to a double digit. Inflation which stood at 9.1% in Nov. 2010, eased considerably to 8.6% in December 2010 but reverted to 9.1% in January 2011, mainly on the account of the 30% increased in the price of petroleum products announced in the first week of January by the National Petroleum Authority (NPA) which resulted in the rise of transportation fares and corresponding increased in food prices. Two key factors that could trigger the rise in inflation figures at the beginning of the third quarter of 2011 are firstly, the full implementation of the Single Spine Salary Structure (SSSS). In March 2011 when the Single Spine Salary Structure was about 60% implemented, the Finance Minister lamented an increased in the Government wage bill. With the migration of the other public sector workers onto the spine, the Government wage bill will increase significantly. This means Government expenditure will rise and this will increase the demand of goods and services and hence increase in inflation. Secondly, the hike in the world prices of crude, which has now reached $125.00 per barrel due to the recent unrest in North Africa and the Middle East. The National Petroleum Authority (NPA) says that despite the fact that Ghana is now an oil producing country, it must increase petrol prices at all cost in order to safeguard the interest of the petroleum industry. If Government is not able to continue subsidizing, then it would be passed onto the consumers and this may also trigger rise in inflation at the beginning of the third quarter of 2011.On this note we suggest that although crude oil prices on the international market continued to pose a risk to Ghana's economy, government has to invest the money accrued from the newly found natural resource in the following ways:

- Investment in productive sector of the economy such as the agricultural and manufacturing sectors.
- Government should invest in public goods such as roads, electricity grids, irrigation
- Works, schools and health clinics. Such infrastructure increases the productivity of the private economy eventually expanding aggregate supply in order to match the increase in aggregate demand from the government expenditures

5.3 RECOMMENDATIONS

The precision of forecast is independent on the simplicity or complexity of the model used. Since the accuracy of forecasted future values is so key in forecasting, we recommend the assessment and the performance of ARIMA $(1, 1, 1)(0, 0, 1)_{12}$ in forecasting Ghana's monthly inflation as a future research topic. Also if government is able to take such mitigating measures under the bullet list above, then this will pave way for policy makers to study inflation situation in Ghana in order to determine other factors that contribute to high inflation rates in the country.

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APPENDIX-A

Table 4.6: Ghana's monthly inflation rates from 1990 to 2010

month	Inflation
1	33.0
2	36.0
3	36.1
4	36.0
5	35.6
6	36.4
7	39.0
8	40.2
9	41.4
10	39.3
11	37.2
12	35.9
13	30.4
14	26.6
15	24.9
16	22.3
17	19.8
18	17.3
19	15.3
20	14.6

Month	Inflation
21	13.2
22	14.0
23	12.9
24	10.3
25	8.7
26	7.7
27	7.3
28	8.2
29	8.9
30	8.4
31	10.2
32	11.7
33	11.2
34	11.7
35	12.6
36	13.3
37	21.5
38	23.0
39	23.0
40	23.0

Month	Inflation
41	23.9
42	26.0
43	25.2
44	25.2
45	26.9
46	26.5
47	26.6
48	27.7
49	22.8
50	22.0
51	21.5
52	21.1
53	21.0
54	20.9
55	22.3
56	23.7
57	26.1
58	29.4
59	31.7
60	34.2

Month	Inflation
61	35.6
62	38.4
63	43.6
64	49.9
65	56.1
66	61.9
67	67.2
68	69.9
69	69.8
70	69.1
71	70.2
72	70.8
73	69.2
74	68.0
75	64.8
76	60.3
77	54.2
78	48.4
79	42.6
80	39.2

Month	Inflation
81	36.5
82	34.3
83	33.2
84	32.7
85	31.5
86	30.6
87	29.2
88	29.1
89	29.6
90	29.0
91	29.2
92	28.2
93	27.7
94	27.4
95	24.2
96	20.8
97	19.8
98	19.6
99	20.3
100	23.1

Month	Inflation
101	22.9
102	21.8
103	18.7
104	18.6
105	17.4
106	17.1
107	16.2
108	15.7
109	15.3
110	15.0
111	13.7
112	10.2
113	9.4
114	10.3
115	12.7
116	12.0
117	11.8
118	12.6
119	13.2
120	13.8

Month	Inflation
121	14.3
122	14.9
123	15.6
124	17.5
125	18.7
126	19.8
127	22.1
128	26.6
129	32.3
130	37.4
131	39.5
132	40.5
133	40.9
134	40.1
135	41.9
136	39.5
137	37.9
138	36.8
139	34.9
140	32.0

Month	Inflation
141	28.3
142	25.6
143	23.7
144	21.3
145	19.9
146	18.3
147	16.0
148	14.9
149	14.3
150	13.7
151	13.5
152	13.1
153	12.9
154	13.2
155	14.0
156	15.2
157	16.3
158	29.4
159	29.9
160	30.0

Month	Inflation
161	29.8
162	29.6
163	29.0
164	27.7
165	26.8
166	24.6
167	23.8
168	23.6
168	22.4
170	11.3
171	10.5
172	11.2
173	11.2
174	11.9
175	12.4
176	12.9
177	12.6
178	12.4
179	12.3
180	11.8

Month	Inflation
181	11.6
182	14.0
183	16.7
184	16.6
185	16.3
186	15.7
187	14.9
188	14.7
189	14.9
190	15.4
191	15.3
192	13.9
193	12.8
194	12.3
195	11.3
196	11.2
197	11.7
198	11.4
199	12.9
200	12.6

Month	Inflation
201	11.7
202	10.9
203	10.7
204	10.9
205	10.9
206	10.4
207	10.2
208	10.5
209	11.0
210	10.7
211	10.1
212	10.4
213	10.2
214	10.1
215	11.4
216	12.7
217	12.8
218	13.2
219	13.8
220	15.3

Month	Inflation
221	16.9
222	18.4
223	18.3
224	18.1
225	17.9
226	17.3
227	17.4
228	18.1
229	19.9
230	20.3
231	20.5
232	20.6
233	20.1
234	20.7
235	20.5
236	19.7
237	18.4
238	18.0
239	16.9
240	16.0

Month	Inflation
241	14.8
242	14.2
243	13.3
244	11.7
245	10.7
246	9.5
247	9.5
248	9.4
249	9.4
250	9.4
251	9.1
252	8.6

APPENDIX –B

Minitab Output For SARIMA (1, 1, 1) $(0, 0, 1)^{12}$

Table 4.7.:ARIMA(1,1,1)(0,0,1)12 MODEL ESTIMATES

Estimates at each iteration				
Iteration	SSE	Parameters		
0	1124.51	0.100	0.100	0.100
1	769.58	0.240	-0.040	0.250
2	703.87	0.390	0.073	.306
3	632.68	0.540	0.182	0.387
4	560.06	0.690	0.281	0.517
5	520.53	0.782	0.328	0.667
6	515.15	0.803	0.327	0.736
7	515.04	0.798	0.322	0.743
8	515.04	0.796	0.320	0.745
9	515.04	0.796	0.319	0.746
10	515.04	0.796	0.318	0.746

Relative change in each estimate less than 0.0010

APPENDIX -C

Table 4.8 FINAL ESTIMATES OF PARAMETERS OF SARIMA$(1, 1, 1)(0, 0, 1)12$ MODEL

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
AR 1	0.7958	0.0597	13.33	0.000
MA 1	0.3189	0.0939	3.40	0.001
SMA 12	0.7446	0.0430	17.31	0.000

Differencing: 1 regular difference

Number of observations: Original series 252, after differencing 251

Residuals: SS = 499.561 (back forecasts excluded)

MS = 2.014 DF = 248

Modified Box-Pierce (Ljung-Box) Chi-Square statistic				
Lag	12	24	36	48
Chi-Square	4.3	13.3	24.4	33.1
DF	9	21	33	45
P-Value	0.893	0.898	0.862	0.906

APPENDIX –D

Table 4.9 12 periods ahead forecast from the origin 252 of SARIMA(1,1,1)(0,0,1)12 Model

	95 Percent Limits				
Month	Period	Forecast	Lower	Upper	Actual
January	253	8.4059	5.6208	11.1909	9.10
February	254	8.2471	3.2796	13.2146	9.16
March	255	8.2081	1.0381	15.3781	9.13
April	256	8.4941	-0.8625	17.8508	9.02
May	257	8.5709	-2.9262	20.0679	N/A
June	258	8.6232	-4.9495	22.1959	N/A
July	259	8.6486	-6.9254	24.2227	N/A
August	260	9.2634	-8.2337	26.7605	N/A
September	261	10.3801	-8.9616	29.7218	N/A
October	262	11.0682	-10.0416	32.1780	N/A
November	263	11.5643	-11.2403	34.3689	N/A
December	264	12.0151	-12.4150	36.4451	N/A

APPENDIX –E

Figure 4.4 ACF of Residuals for Ghana's Inflation Data

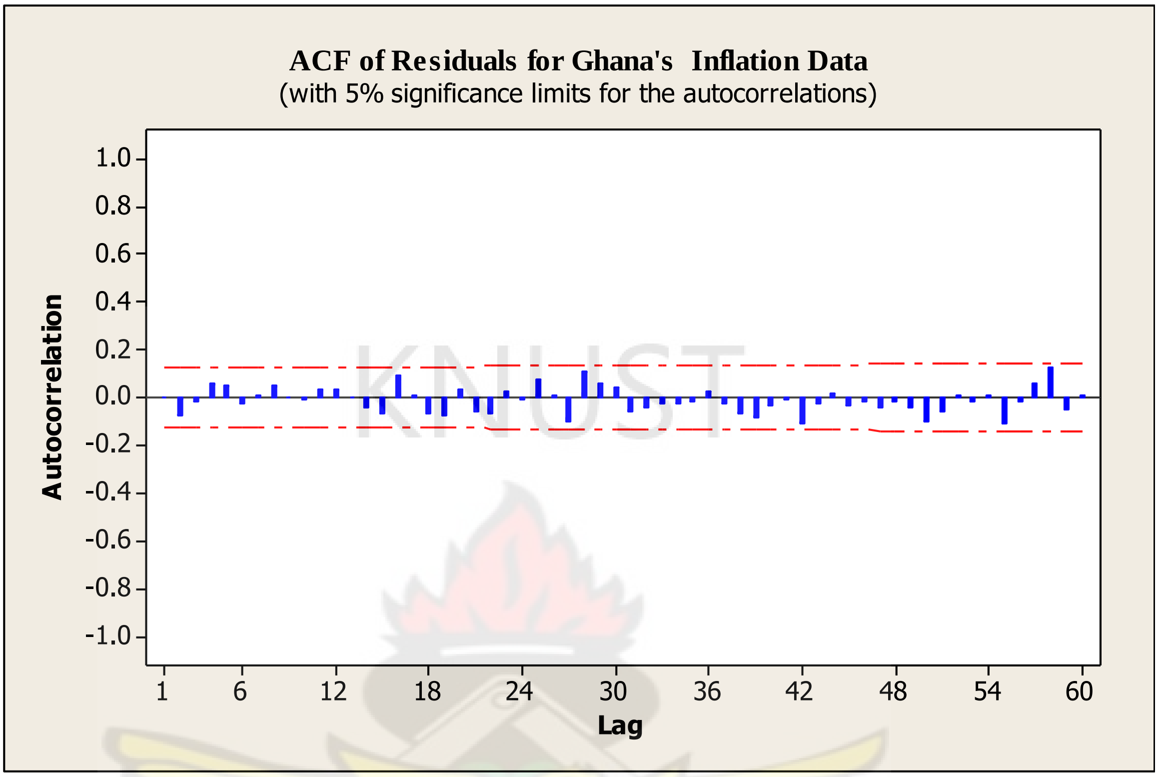
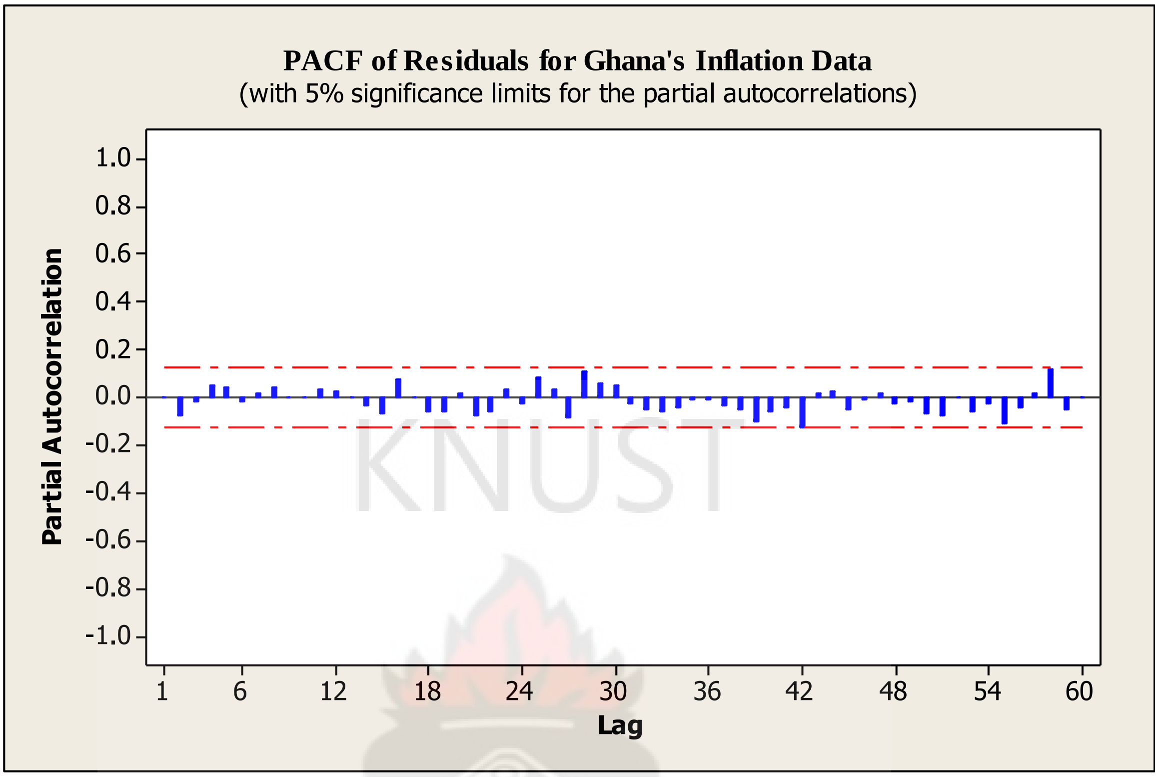


Figure 4.5 PACF OF RESIDUALS FOR Ghana's Inflation Data



APPENDIX F

Figure 4.6 Time Series Plot for Original data and Forecasts