Investigating the Pattern of Inflation Rates in Nigeria using Seasonal Auto-Regressive Integrated Moving Average (SARIMA) Model

1Oladapo D.I., 2Ajewole K.P., 3Ayanlowo E.A.
1,3Department of Mathematical Science, Adeleke University, Ede, Osun State, Nigeria. 2Department of Statistics, Ekiti State University, Ado-Ekiti, Ekiti State, Nigeria.

Abstract: Nigeria has been faced with the macroeconomic problem of inflation for a long period of time. The problem slows down the economic growth in this country. As we all know, inflation is one of the major economic challenges facing most countries in the world especially those in Africa including Nigeria.

Therefore, forecasting inflation rates in Nigeria becomes very important for the government to design economic strategies or effective monetary policies to combat any unexpected high inflation in the country.

This study utilizes seasonal autoregressive integrated moving average model (SARIMA) to forecast inflation rates in Nigeria using monthly inflation data from January 1999 to December 2018. We discover that SARIMA \((1, 1, 1) \times (0, 0, 1)_{12}\) can represent very well in the data behavior and the forecasting of inflation rate in Nigeria.

The research revealed that the inflation of Nigeria is non-stationary and based on the selected model, we forecast twelve (12) months inflation rates of Nigeria outside the sample period (i.e. from January 2019 to December 2019).

Keywords: ARIMA, Forecasting, Inflation, Model, SARIMA

I. Introduction

It is believed that Nigeria is a developing country. Out of all the micro and macro economy variables which affect the growth of the economy, the effect of inflation is likely to be significant since inflation is created locally in the case of Nigeria (i.e. there is general rise in price of goods in Nigeria at the devaluation of naira) while we import inflation due to over reliance on imported goods from inflation affected countries.

Inflation is the rate at which the general level of prices for goods and services is rising and, consequently, the purchasing power of currency is falling. As prices rise, a single unit of currency loses value as it buys fewer goods and services. This loss of purchasing power impacts the general cost of living for the common public which ultimately leads to a deceleration in economic growth. The consensus view among economists is that sustained inflation occurs when a nation's money supply growth outpaces economic growth. To combat this, a country's appropriate monetary authority, like the central bank, is expected to take the necessary measures to keep inflation within permissible limits and keep the economy running smoothly.

Inflation is a problem in all facets of life and in all economic entities. Government of any nation is saddled with the responsibility of ensuring that her plans and programmes are not frustrated by unpredictable and galloping prices. Every firm desires a stable macro-economic environment that is devoid of unrepentant price change that can bring about reliable forecast and planning. An individual also strives that he is not worse off by unexpected price increase. All these bring home the need to explore the study of inflation so as to form a timeless and dependable model of its tendency (Taiwo, 2011).

Sloman and Kevin (2007) explain that inflation may be either demand pull inflation or cost push inflation. Demand pull inflation is caused by persistent rises in aggregate demand thus the firms responding by raising prices and partly by increasing output. Cost push inflation is associated with persistent increase in the costs experienced by firms. Firms respond by raising prices and passing the costs on to the consumer and partly cutting back on production. Hendry (2006) agrees that inflation is the resultant of many excess demands and supplies in the economy.

Tucker (2007) observed that there are many measures of inflation, because there are many different price indices relating to different sectors of the economy. Two widely known indices for which inflation rates are reported in many countries are the Consumer Price Index (CPI) which measures prices that affect typical consumers, and the Gross Domestic Product (GDP) deflator, which measures prices of locally-produced goods and services.

II. Materials and Method

The relevant data needed for this work is monthly data on inflation rate (1999-2018). These data were obtained from the Central Bank of Nigeria (CBN) and the National Bureau of Statistics (NBS). For the Seasonal Autoregressive Integrated moving Average modeling, we will be using two Statistical packages (SAS and E-view) because E-view is an econometric software for data analysis and this study deals with inflation which is an economic factor while SAS will be mostly used for data visualization in this study.
In this study, a univariate Box-Jenkins Methods (Box et al., 1994) in particular, a seasonal autoregressive integrated moving average (ARIMA) model is used, since most of the economic series are non-stationary in nature.

A. Autoregressive (AR) Models

Autoregressive models are based on the idea that the current value of the series \(x_t\) can be explained as a function of \(p\) past values, \(x_{t-1}, x_{t-2}, ..., x_{t-p}\) where \(p\) determines the number of steps into the past needed to forecast the current value. An autoregressive model of order \(p\), abbreviated AR (\(p\)) can be written as:

\[
x_t = \varnothing_1 x_{t-1} + \varnothing_2 x_{t-2} + \cdots + \varnothing_p x_{t-p} + \epsilon_t
\]

(1)

where \(x_t\) is stationary series, \(\varnothing_1, \varnothing_2, ..., \varnothing_p\) are the parameters of the AR \((\varnothing_0 \neq 0), (\varnothing_p \neq 0)\) and the \(\epsilon_t\) are typically assumed to be uncorrelated \((0, \sigma^2)\). Unless otherwise stated, we assume that \(\epsilon_t\) is a Gaussian white noise series with mean zero and variance \((\sigma^2)\). The highest order \(p\) is referred to as the order of the model.

The model in lag operators takes the following form:

\[
(1 - \varnothing_1 B - \varnothing_2 B^2 - \cdots - \varnothing_p B^p)x_t = \epsilon_t
\]

(2)

where the lag (backshift) operator \(B\) is defined as: \(B^p x_t = x_{t-p}, \ p = 0,1,2,...\)

More concisely we can express the model as:

\[
\varnothing(B)x_t = \epsilon_t
\]

(3)

The autoregressive operator \(\varnothing(B)\) is defined to be

\[
\varnothing(B) = 1 - \varnothing_1 B - \varnothing_2 B^2 - \cdots - \varnothing_p B^p
\]

(4)

The values of \(\varnothing\) which make the process stationary are such that the roots of \(\varnothing(B) = 0\) lie outside the unit circle in the complex plane (Chatfield, 1991). If all roots of \(\varnothing(B)\) are larger than one in absolute value, then the process is a stationary process satisfying the autoregressive equation and can be represented as:

\[
x_t = \sum_{j=0}^{\infty} \psi_j \epsilon_{t-j}
\]

(5)

The coefficients \(\psi_j\) converge to zero, such that \(\sum_{j=0}^{\infty} |\psi_j| < \infty\). If some roots are “exactly” one in modulus, no stationary solution exists.

A plot of the ACF of a stationary AR \((p)\) model show a mixture of damping sine and cosine patterns and exponential decays depending on the nature of its characteristic roots.

Another characteristics feature of AR \((p)\) models is that the partial autocorrelation function defined as \(PACF_j = cor. (x_t, x_{t-j}) / x_{t-1}, x_{t-2}, ..., x_{t-j+1}\) becomes “exactly” zero for values larger than \(p\) (Tsay, 2005).

B. Moving average (MA) Models

As an alternative to the autoregressive representation in which the \(x_t\) on the left-hand side of the equation are assumed to be combined linearly, the moving average model of order \(q\), abbreviated as MA\((q)\), assumes the white noise \(\epsilon_t\) on the right-hand side of the defining equation are combined linearly to form the observed data.

A series \(x_t\) is said to follow a moving average process of order \(q\) or simply MA \((q)\) process if

\[
x_t = \omega_1 w_{t-1} + \omega_2 w_{t-2} + \cdots + \omega_q w_{t-q}
\]

(6)

where \(\omega_1, \omega_2, ..., \omega_q\) are the MA parameters. MA\((q)\) models immediately define stationary, every MA process of finite order is stationary (Diebold et al., 2006). In order to preserve a unique representation, usually the requirement is imposed that all roots of \(\omega(B) = 1 + \omega_1 B + \omega_2 B^2 + \cdots + \omega_q B^q = 0\) are greater than one in absolute value. If all roots of \(\omega(B) = 0\) lie outside the unit circle, the MA process has an autoregressive representation of generally infinite order \(\sum_{j=0}^{\infty} \psi_j x_{t-j} = w_t\) with \(\sum_{j=0}^{\infty} |\psi_j| < \infty\) MA process as with an infinite order autoregressive representation are said to be invertible.

A characteristics feature of MA\((q)\) is that their ACF, \(\rho_j\) becomes statistically insignificant after \(j = q\). The property of the ACF should be reflected in the correlogram, which should cut off after \(q\). The PACF converges to zero geometrically.
C. Autoregressive Moving Average (ARMA)

We now proceed with the general development of autoregressive, moving average, and mixed autoregressive moving average (ARMA) models for stationary time series. In most cases, it is best to develop a mixed autoregressive moving average model when building a stochastic model to represent a stationary time series. The order of an ARMA model is expressed in terms of both $p$ and $q$. The model parameters relate to what happens in period $t$ to both the past values and the random errors that occurred in past time periods. A general ARMA model can be written as:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + \omega_t + \theta_1 \omega_{t-1} + \theta_2 \omega_{t-2} + \cdots$$

with the following definition of the operators

$$\phi(B)x_t = \theta(B)\omega_t$$

Equation (16) of the time series model will be simplified by a backward shift operator $B$ to obtain

$$\phi(B)x_t = \theta(B)\omega_t$$

The ARMA model is stable, that is it has a stationary solution if all roots of $\phi(B) = 0$ are larger than one in absolute value. The representation is unique if all roots of $\phi(B) = 0$ lie outside the unit circle where $\phi(B) = 0$ and $\theta(B) = 0$ do not have common roots. Stable ARMA models always have an infinite order MA representation. If all roots of $\phi(B)$ are larger than one in absolute value, it has an infinite order AR representation. The process is invertible only when the roots of $\theta(B)$ lie outside the unit circle. Furthermore, a process is said to be causal when the roots of $\phi(B)$ lie outside the unit circle. To have ARMA($p$, $q$) model, both ACF and PACF should show a pattern of decaying to zero. The autocorrelation of an ARMA($p$, $q$) process is determined at greater lags by the AR($p$) part of the process as the effect of the MA part dies out. Thus, eventually the ACF consists of mixed damped exponentials and sine terms. Similarly, the partial autocorrelation of an ARMA($p$, $q$) process is determined at greater lags by the MA($q$) part of the process. Thus, eventually the partial autocorrelation function will also consist of a mixture of damped exponentials and sine waves.

D. Autoregressive Integrated Moving Averages (ARIMA) Models

Autoregressive integrated moving average (ARIMA) models are specific subset of univariate modeling, in which a time series is expressed in terms of past values of itself (the autoregressive component) plus current and lagged values of a white noise error term (the moving average component). ARIMA models are univariate models that consist of an autoregressive polynomial, an order of integration($d$) and a moving average polynomial.

A process ($x_t$) is said to be an autoregressive integrated moving average process, denoted by $ARIMA(p,d,q)$ if it can be written as:

$$\phi(B)^d x_t = \theta(B)\omega_t$$

where $\phi(B)^d = (1-B)^d$ with $\phi(B)$ and $\theta(B)$ are polynomials. The resulting pure seasonal autoregressive moving average model, say, $ARIMA(P, Q, S)$, then takes the form (Shumay and Stoffer, 2010):

$$\Phi_p(B^S)x_t = \Theta_q(B^S)\omega_t$$

with the following definition of the operators

$$\Phi_p(B^S)x_t = \Theta_q(B^S)\omega_t$$

Where $\alpha$ is a parameter related to the mean of the process $x_t$, by $\alpha = \mu(1 - \phi_1 - \cdots - \phi_p)$ and this process is called a white noise process, that is, a sequence of uncorrelated random variables from a fixed distribution (often Gaussian) with constant mean $E\{x_t\} = \mu$ usually assumed to be “zero” and constant variance. If $d = 0$, it is called $ARIMA(p, q)$ model while when $d = 0$ and $q = 0$, it is referred to as autoregressive of order $p$ model and denoted by AR ($p$). When $p = 0$ and $d = 0$, it is called Moving Average of order $q$ model, and is denoted by MA ($q$).

E. Seasonal ARIMA (SARIMA)

Here we introduce several modifications made to the ARIMA model to account for seasonal and non-stationary behavior. Often, the dependence on the past tends to occur most strongly at multiples of some underlying seasonal lags. Seasonal ARIMA (SARIMA) is used when the time series exhibits a seasonal variation. Natural phenomena such as temperature and rainfall have strong components corresponding to seasons. Hence, the natural variability of many physical, biological, and economic processes tends to match with seasonal fluctuations. Because of this, it is appropriate to introduce autoregressive and moving average polynomials that identify with seasonal lags. The resulting pure seasonal autoregressive moving average model, say, $ARIMA(P, Q, S)$, then takes the form (Shumay and Stoffer, 2010):

$$\Phi_p(B^S)x_t = \Theta_q(B^S)\omega_t$$

with the following definition of the operators

$$\Phi_p(B^S)x_t = \Theta_q(B^S)\omega_t$$
are the seasonal autoregressive operator and the seasonal moving average operator of orders P and Q, respectively, with seasonal period S. Analogous to the properties of non-seasonal ARMA models, the pure seasonal ARMA($p, Q$) is causal only when the roots of $\Phi_p(B^S)$ lie outside the unit circle, and it is invertible only when the roots of $\Theta_Q(B^S)$ lie outside the unit circle. In general, we can combine the seasonal and non-seasonal operators into a multiplicative seasonal autoregressive moving average model, denoted by ARIMA($p, d, q$) × ($P, D, Q$)S and write as the overall model as:

$$\Phi_p(B^S)\Theta_p(B^S)\Theta(B)w_t = \Phi_Q(B^S)\Theta(B)w_t$$

A seasonal autoregressive notation ($P$) and a seasonal moving average notation ($Q$) will form the multiplicative seasonal autoregressive integrated moving average model, denoted by ARIMA($p, d, q$) × ($P, D, Q$)S, of Box and Jenkins (1976) and is given by:

$$\Phi_p(B^S)\Theta(B)\nabla^D_x t = \alpha + \Theta_Q(B^S)\Theta(B)w_t$$

where $w_t$ is the usual Gaussian white noise process. The ordinary autoregressive and moving average components are represented by polynomials $\Theta(B)$ and $\Theta(B)$ of orders $p$ and $q$, respectively and the seasonal autoregressive and moving average components by $\Phi_p(B^S)$ and $\Theta_Q(B^S)$ of orders $p$ and $Q$. The ordinary and seasonal difference components can be written as $\nabla^d = (1 - B)^d$ and $\nabla^D_x = (1 - B^S)^D$.

### F. Building ARIMA Models

To identify a perfect ARIMA model for a particular time series data, Box and Jenkins (1976) proposed a methodology that consists of four phases: i) Model identification; ii) Estimation of model parameters; iii) Diagnostic checking for the identified model and iv) Application of the model (i.e. forecasting).

### III. Analysis

General equation of the chosen model is:

$$\Phi_p(B^{12})\Phi_p(B)(1 - B)^4(1 - B^{12})\Theta(B)w_t$$

After the modification of the equation and substitution of estimated values, we get the following equation and it describes the dynamics of our time series:

$$u_t = (1 + 0.41L)(1 - 0.61L^{12})u_t = (1 - 0.19L)(1 + 0.96L^{12})\epsilon_t$$

In this section, we assume we have $n$ observations $x_1, ..., x_n$ from a causal and invertible Gaussian ARMA($p, q$) × ($P, Q$)S process in which initial order of parameters, $p, q, P$ and $Q$ are known. Our goal is to estimate the value of parameters: $\theta_1, ..., \theta_p, \theta_1, ..., \theta_p, \Phi_1, ..., \Phi_p, \Theta_1, ..., \Theta_p$.

For $SARIMA(1,1,1) \times (1,0,1)_{12}$ model, the fitted model is given as:

$$X_t = -0.095 + u_t$$

$$u_t = (1 + 0.41L)(1 - 0.61L^{12})u_t = (1 - 0.19L)(1 + 0.96L^{12})\epsilon_t$$

where $AIC = 3.35863, SIC = 3.47235$ and $HQC = 3.40483$

For $SARIMA(1,1,1) \times (0,0,1)_{12}$ model, the fitted model is obtained as:

$$X_t = -0.008 + u_t$$

$$(1 + 0.08L)u_t = (1 + 0.28L)(1 - 0.97L^{12})\epsilon_t$$

where $AIC = 3.27004, SIC = 3.35571$ and $HQC = 3.30485$.

While for $SARIMA(1,1,1) \times (1,0,0)_{12}$ model, the fitted model is given as:

$$X_t = -0.030 + u_t$$

$$(1 + 0.02L)(1 - 0.23L^{12})u_t = (1 + 0.29L)\epsilon_t$$

where $AIC = 3.63860, SIC = 3.72958$ and $HQC = 3.67556$.

and for $SARIMA(0,1,1) \times (1,0,1)_{12}$ model, the fitted model is obtained as:

$$X_t = -0.074 + u_t$$
(1 - 0.62L^{12})u_t = (1 + 0.21L)(1 - 0.96L^{12})e_t \quad (19)

where AIC = 3.34805, SIC = 3.43856 and HQC = 3.38482.

In order to select the best model to analyze monthly inflation rate in Nigeria, the AIC and SBC were used to compare selected models fit. The model with the smaller information criteria is said to fit the data better. Since SARIMA (1,1,1) \times (0,0,1)_{12} model has the lowest AIC and SBC, then this model is believed to estimate Nigerian monthly inflation rate better than the other models.

A. Diagnostic Checking

In this section, we shall assess how well the selected model fits Nigerian inflation rate. If the model fits the data well, the residuals of the fitted model are random (Chatfield, 1991). In ARIMA modeling, the selection of the best model to analyze data is directly related to how well the residual analysis performs (Kadri et al., 2005). Therefore, several diagnostic statistics and plots of the residuals can be used to examine the goodness of fit of the selected model to the data.

![Residual Normality Diagnostics for inflation](Image)

**Figure 1**

Figures 1 above shows the histograms and QQ-plot of the residuals. As expected, the curves significantly reflect a normal distribution.

Test statistic values of the Breusch and Pagan (B-P) test for the homoscedasticity of the residuals are also presented in Table 11 (Appendix). All calculated values are found to be smaller than the respective critical values, indicating that the residual variance is constant. Therefore, the hypothesis that the residuals are white noise cannot be rejected, indicating that the fitted model is adequate. That is, SARIMA (1,1,1) \times (0,0,1)_{12} model is adequate for modeling Nigeria inflation rate.

To test whether the residual from the fitted model come from normally distributed series, we use histogram and QQ-plot of the residual test. The histogram and QQ-plot of the residual shown in Figures 4.3 and 4.4 above, show that the residuals come from a normal distribution.

B. Forecasting

Since the model diagnostic tests show that all the parameter estimates are significant and the residual series is white noise, the estimation and diagnostic checking stages of the modeling process is complete. We can now proceed to forecasting the inflation series with fitted SARIMA (1,1,0) \times (0,1)_{12} model. Forecasting refers to the process of predicting future inflation values from a known time series. In this study, the forecasting is performed as follows:

According to (23), the SARIMA (1,1,1) \times (0,0,1)_{12} model can be written as

\[ (1 - \Phi_1 B^1) \Theta_1^1 X_t = (1 + \Theta_1 B^1)(1 + \Theta_{12} B^{12})e_t \quad (20) \]

This equation can also be multiplied out and rewritten in a form that is used in forecasting as shown in (42) below.

\[ X_t = \Phi_1(X_{t-1}) + e_t + \Theta_1 e_{t-1} + \Theta_{12} e_{t-12} \quad (21) \]

where \( B^1 X_t = X_{t-1} \).

The above equation can be re-expressed as:

\[ X_{t+m} = \Phi_1(X_{t+m-1}) + e_{t+m} + \Theta_1 e_{t+m-1} + \Theta_{12} e_{t+m-12} \quad (22) \]

In order to forecast one period ahead that is \( X_{t+1} \), (43) is increased by one unit throughout to become:

\[ X_{t+1} = (1 + \Phi)X_t - \Phi X_{t-1} + e_{t+1} - \Theta_{12} e_{t-11} - \Theta_1 e_t + \Theta_1 \Theta_{12} e_{t-12} \quad (23) \]

The term \( e_{t+1} \) is not known because the expected value of future random errors has been taken as zero. There are 240 data points from January 1999 to December 2018 used to build the SARIMA model.

From table 8, using \( \phi = 0.08, \theta_1 = 0.28, \theta_{12} = 0.97 \) and \( \theta_1 \theta_{12} = 0.2716 \) Thus, (44) is given as
\[ \hat{X}_{t+1} = 1.08X_{240} - 0.08X_{239} + \hat{e}_{t+1} - 0.97\hat{e}_{t-11} - 0.28\hat{e}_t + 0.2716\hat{e}_{t-12} \]  

(24)

In order to forecast inflation for the period 240 (that is, December 2018), (45) is given by

\[ \hat{X}_{240} = 1.08X_{240} - 0.08X_{239} + \hat{e}_{239} - 0.97\hat{e}_{227} - 0.28\hat{e}_{239} + 0.2716\hat{e}_{226} \quad \hat{e}_{240} = 0 \]

The forecast quantity for a year period was gotten using Statistical analysis software.

Once our model has been obtained and its parameters estimated, we can use it to make our prediction. Table 1 and figure 2 respectively below summarizes 12 months’ upfront inflation forecast from January 2019 to December 2019 while detailed statistics is in the appendix.

**TABLE 1. 12-MONTH FORECASTED INFLATION FOR January 2019 TO December 2019**

<table>
<thead>
<tr>
<th>Month(s)</th>
<th>Forecast %</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>11.48</td>
</tr>
<tr>
<td>February</td>
<td>11.51</td>
</tr>
<tr>
<td>March</td>
<td>11.79</td>
</tr>
<tr>
<td>April</td>
<td>11.87</td>
</tr>
<tr>
<td>May</td>
<td>12.11</td>
</tr>
<tr>
<td>June</td>
<td>12.06</td>
</tr>
<tr>
<td>July</td>
<td>12.07</td>
</tr>
<tr>
<td>August</td>
<td>11.89</td>
</tr>
<tr>
<td>September</td>
<td>11.85</td>
</tr>
<tr>
<td>October</td>
<td>11.73</td>
</tr>
<tr>
<td>November</td>
<td>11.71</td>
</tr>
<tr>
<td>December</td>
<td>11.54</td>
</tr>
</tbody>
</table>

**Figure 2** Table forecast of the Nigeria inflation

**Figure 2**

**C. Forecasting Accuracy Evaluation**

If the fitted SARIMA (1,1,1) × (1,1,0) sub-model has to perform well in forecasting, the forecast error will be relatively small. The accuracy of forecasts is usually measured using root mean square error (RMSE), mean absolute error (MAE), Mean absolute percentage error (MAPE) and Theil’s inequality coefficient (Theil-U). The result shows that the Mean Absolute Percentage Error (MAPE) turns out to be 3.56%, which is relatively less than 4% and Theil’s inequality coefficient (U-statistic) turn out to be 0.018, which is relatively close to zero. Besides this result, the bias and variance proportion are also very small, which are 0.047 and 0.001, respectively. Thus, measures indicate that the forecasting inaccuracy is low.

**IV. Discussion**

The purpose of this study is to analyze the structure and pattern of Nigeria monthly inflation rates from January 1999 – December 2018 using seasonal autoregressive integrated moving average (SARIMA). The aim and objectives of this research work are to examine and explore the monthly inflation rates in Nigeria by constructing and analyzing the model. We as well, forecast in-sample values and determine the forecast performance of the models used. The findings from this study show that the aim and objectives of the research were achieved and the findings are outlined below:
The time plots showed that each year there is upward increase in the trend and suggests that the given time series is non-stationary. The movement is secular in nature and expect a small shift in the movement in mid-2005. The augmented dickey fuller and Phillips-Persons test show that Nigeria Inflation rate is stationary at the first difference, that is $I(1)$. The SARIMA model identified and fitted is $SARIMA(1,1,1) \times (0,0,1)_{12}$. This model was used to estimate parameters using Akaike Information Criterion (AIC) and Schwartz’s Bayesian Criterion (SBC), $SARIMA(1,1,1) \times (0,0,1)_{12}$ said to estimate Nigerian monthly inflation rate better than the other models because it has the lowest values.

The forecasted values of future Nigerian inflation between January 2019-December 2019 was obtained using the model i.e. $SARIMA(1,1,1) \times (0,0,1)_{12}$. The forecasting results in general revealed a decreasing pattern of inflation rates over forecast period of 12 months.

**Conclusion**

In this study, we made use of some Nigerian inflation rates from January, 1999 to December, 2019 to determine the structure and pattern of the Inflation rates using Seasonal Autoregressive Moving Integrated Average (SARIMA) model following the Box Jenkins approach. Four models were considered and in order to select the best model to analyze monthly inflation rate in Nigeria, the AIC and SBC were used to compare selected models fit. The model with the smaller information criteria is then said to be the best model. Therefore $SARIMA(1,1,1) \times (0,0,1)_{12}$ model was picked as the champion model to estimate Nigerian monthly inflation rate better than the other models.

This study had shown the forecast performance from January, 2019 to December, 2019. In the light of the forecast results, policy makers should gain insight into more appropriate economic and monetary policy in order to combat such increase in Inflation rate which may occur in the month of July, 2019 causing unnecessary panic and can probably lead to unexpected increase in the inflation rate of Nigeria.

Finally, this study has shown that the inflation rates in Nigeria are non-stationary. Then, if all the recommendations below are considered by the government, policy makers, ministries, financial organizations and the private sector, Nigerian economy will develop and grow rapidly. Monetary policy must be transparent and corruption must be properly checked. Nigerian government needs to give room to statistician to participate more in the planning and execution of government economic policies.

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