Modelling and forecasting inflation rate in Nigeria using ARIMA models

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Abstract

This study modelled and forecast inflation in Nigeria using the monthly Inflation rate series that spanned January 2003 to October 2020 and provided three years monthly forecast for the inflation rate in Nigeria. We examined 169 ARMA, 169 ARIMA, 1521 SARMA, and 1521 SARIMA models to identify the most appropriate model for modelling the inflation rate in Nigeria. Our findings indicate that out of the 3380 models examined, SARMA (3, 3) x $(1, 2)_{12}$ is the best model for forecasting the monthly inflation rate in Nigeria. We selected the model based on the lowest Akaike Information Criteria (AIC) and Schwarz Information Criterion (SIC) values, volatility, goodness of fit, and forecast accuracy measures, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The AIC and SIC of the model are 3.3992 and 3.5722, respectively with an adjusted R^2 value of 0.916. Our diagnostic tests (Autocorrelation and Normality of Residuals) and forecast accuracy measures indicate that the presented model, SARMA $(3, 3)(1, 2)_{12}$, is good and reliable for forecasting. Finally, the three years monthly forecast was made, which shows that the Inflation rate in Nigeria would continue to decrease but maintain a 2 digits value for the next two years, but is likely to rise again in 2023. This study is of great relevance to policymakers as it provides a foresight of the likely future inflation rates in Nigeria.

Keywords: Inflation; Modelling, Forecasting; ARMA; ARIMA; SARMA; SARIMA;

JEL Classification: C22 C52, C53, E31, E37, E47

1. Introduction

Inflation can be characterized as the industrious and nonstop ascent in the overall prices of any given commodity in an economy. Inflation is the depreciation in the purchasing ability of a particular currency after some time. A quantitative gauge of the rate at which the decrease in buying power happens can be reflected in the expansion of a normal value level of a basket of chosen goods and services in an economy throughout some timeframe. The ascent in the overall degree of prices regularly communicated as a percentage implies that a unit of money successfully purchases short of what it did in earlier periods. Inflation can be stood out from deflation, which happens when the purchasing power of money increments and prices decrease (Jason Fernando, 2020).

While it is difficult to quantify the value changes of each item over the long run, human requirements broaden much past a couple of such items. People need a major and differentiated arrangement of items just as a large group of services for carrying on with an agreeable life. They incorporate commodities like food metal, grains, and fuel, utilities like power and transportation, and other services such as medical care, amusement, and work. Inflation plans to gauge the general effect of cost changes for a differentiated arrangement of items and services and takes into account a solitary worth portrayal of the expansion in the value level of services in the economy throughout some undefined time frame.

In this day and age, information on what helps gauge inflation is significant. Policymakers of a country can get earlier signs about conceivable future inflation through forecasting the inflation rate (Nyoni, 2018). It is conceivable to credit the hike in the inflation rate of Nigeria to some factors, for example, low development rate, exorbitant costs of imported items, continuous devaluation of the currency in the foreign exchange market, and presumably outer variables like prices of crude oil. Since the stability and dependability of prices of goods and services includes one of the vital goals of monetary policy (Hadrat et al, 2015), it is dependent upon the policymakers to have a foresight of the possible future inflation rate. To accomplish this feat, a precise forecasting capacity is pertinent. Forecasting Inflation is not just a helpful guide to policy making, however, it additionally assumes a prevailing function in a circumstance where a nation is rehearsing an inflation focusing system as it can make policymakers aware of intense choice when inflation goes astray from its main focus (Iftikhar and Iftikhar-ul-amin, 2013). The fact that monetary policies are related to significant lags, it is therefore pertinent for policymakers to plan ahead of time. This fact further ignites the significance of getting inflation rate forecast that are accurate to a significant degree (Mandalinci, 2017; Nyoni, 2018).

The historical backdrop of the high inflation rate in the country could be tracked as far back as the Udoji Commission of 1974, who proposed an improved compensation structure for government employees without thinking about the effect. Inflation has been one of the most known monetary difficulties on the planet, particularly in developing countries (Jere and Siyanga, 2016). The monetary experts in Nigeria are facing challenges of keeping up stable inflation and guaranteeing high economic development.

Nigeria faced a hike inflationary rate in the 1990s as a result of the high fiscal expansion and monetary growth in the 1990s. The inflation rate flooded to 57.16% in 1993 and the highest inflation rate (72.84%) was recorded in 1995. Be that as it may, in 1997, it diminished to 8.5%. The rate further reduced to 6.93% in the year 2000. Having accomplished a unit value inflation rate, the monetary authority in Nigeria as well as the government could not continue the pattern as inflation expanded to 19% in 2002 (Nyoni et al., 2018). The inflation rate further increased to 23.8% by December 2003. The highest inflation rate recorded in 2004 was 24.8% in February. However, by December 2004, the rate had dropped to 10%. The inflation rate was 11.6% and 8.5% at the end of 2005 and 2006, respectively. The nation recorded its lowest inflation rate (3.0%) in July 2007 but increased to 6.6% at the end of that year. The inflation rate was 15.1% in December 2008; 13.9% at the end of 2009; 11.8% in December 2010, and respectively 10.3%, 12%, 8%, 8%, 9.55%, and 18.55% at the end of 2011, 2012, 2013, 2014, 2015 and 2016. In December 2017, the inflation rate was at 15.9%. The inflation rate further dropped to 11.44% by December 2018, but rise to 11.98% by December 2019. As of October 2020, the inflation rate has risen to 14.23% (CBN, 2020).

The latest advancements on the planet have made forecasting of inflation to be necessary and significant. The significance of forecasting inflation rate in developing countries had made researchers like Balcilar et al, 2015; Chen et al, 2014; Pincheira and Medel 2015; Mandalinci 2017; Medel et al, 2016; Aron and Muellbauer, 2012, and Altug and Cakmakli 2016 to conduct researches on the inflation rate. The aftermath of the high inflation rate and the delay of monetary policies propose the need to look into the inflation rate and to propose a means of maintaining stable inflation in the country. Different methods had been used by the researcher to model the inflation rate in Nigeria. Among the studies on inflation in Nigeria that utilized ARIMA models are Etuk et al, 2012; Adebiyi et al., 2010; Okafor and Shaibu 2013; Kelikume and Salami 2014; Olajide et al, 2012; Mustapha and Kubalu 2016; and Popoola et al., 2017. SARIMA model was utilized by Doguwa and Alade, 2013, while Otu et al., 2014; and John and Patrick, 2016 combined the ARIMA and SARIMA models. Nyoni and Nathaniel 2019 utilized the ARMA, ARIMA, and GARCH modes to model rates of inflation in Nigeria.

Quite a number of researchers have conducted researches on the inflation rate in Nigeria and across the globe in general. A good number of different methods had been employed in modeling and studying the dynamics, determinants, and effect of the inflation rate on Nigeria economy. Olubusoye and Oyaromade (2008) investigated the major factor that determines inflation in Nigeria. The authors used data that spanned 1970 to 2003, employing the Error Correction Mechanism. Findings of the study indicate that petroleum product prices, inflation expected, and exchange rate significantly affect the inflation trend in Nigeria. Another study by Imimole and Enoma (2011) examined the influence of depreciation in the exchange rate on the inflationary process in Nigeria. The author utilized data that spanned 1986 to 2008 and employed the Autoregressive Distributed Lag (ARDL) model. Major findings of the study showed that real gross domestic product, exchange rate depreciation, inflation inertia, and money supply as the factors that determines Nigeria inflation rate.

John and Patrick (2016) modeled the inflation rate of Nigeria using inflation series that spanned 2000M1 to 2015M6. The study proposed the ARIMA (0, 1, 0) x (0, 1, 1) model, for forecasting Nigeria's inflation because the residuals from the in-sample forecast values was very small in values. Another study by Inam (2017) modelled Nigeria inflation by adopting the VAR model. The study utilized data on the money supply, inflation rate, fiscal deficit, interest rate, real exchange rate, and changes in real output and import prices for the period of 1990 to 2012. Major findings revealed that the previous lag value of inflation significantly influenced the current and the future inflation rate in the country. Mustapha and Kubalu (2016) modeled the inflation rate in Nigeria using the inflation rate series that spanned January 1995 to December 2013. The study found that among the different models examined, ARIMA appears as the most fitted model that can be used in explaining the relationship that exist between past and current inflation rates in Nigeria. Another study by Otu *et al.,* (2014) examined the inflation rate in Nigeria by employing the ARIMA and SARIMA models. The authors used monthly data that spanned the period 2003M11 to 2013M10. The findings of the study indicated that SARIMA shows a better forecast ability for the inflation rate in Nigeria. Kelikume and Salami (2014) modeled Nigeria's inflation rate using monthly data that spanned 2003 to 2012. The authors adopted the VAR and ARIMA models. The findings of the study revealed that The VAR model performed better compared to the ARIMA model in terms of its smaller minimum square error. Okafor and Shaibu (2013) examined the inflation rate dynamics using the inflation series that spanned 1981 to 2010. The author examined different ARIMA models. The study found that ARIMA (2, 2, 3) appears as the best model for the forecasting inflation rate in Nigeria.

Several studies had been conducted on modelling the inflation rate in Africa. A study by Jere and Siyanga (2016) modelled the inflation rate of Zambia. The authors used the inflation series that spanned May 2010 to May 2014. The study employed the Holts exponential smoothing and ARIMA model to the inflation series. The study found that ARIMA (12, 1, 0) model performed better compared to the Holts exponential smoothing. Another study by Ingabire and Mung'atu (2016) modelled the inflation rate of Rwanda using the data that spanned 2000 Q1 to 2015 Q1. The authors employed the ARIMA and VAR models. The findings of the study revealed that ARIMA (3, 1, 4) model performed better than the VAR model in forecasting inflation rate in Rwanda.

Uwilingiyimana, *et al.* (2015) modelled the inflation rate of Kenya using monthly data from 2000 to 2014. The study adopted the ARIMA and GARCH models to predict the future value of the inflation rate in the country. The study found that the combination of ARIMA (1, 1, 12) and GARCH (1, 2) models provide the best predictive result. In contrast, a study by Fwaga et al. (2017) employed the GARCH and EGARCH models to the inflation rate series of Kenya from January 1990 to December 2015. The study concluded that the EGARCH model can best forecast inflation rate in Kenya.

Lidiema (2017) used the monthly inflation rate series of Kenya from November 2011 to October 2016 to modelled and forecast the future inflation rate in Kenya. The study employed the SARIMA and Holt-Winters Triple Exponential Smoothing. The result of the study indicated that the SARIMA Model was proved as the better model for forecasting the inflation rate in Kenya compared to the Holtwinters triple exponential smoothing. Nyoni (2018) modelled the inflation rate of Zimbabwe by adopting the GARCH model. The author used monthly data from July 2009 to July 2018. The findings of the study revealed that AR (1) –IGARCH (1, 1) model is the best for the predicting inflation rate in Zimbabwe. Yusif et al. (2015) modelled the inflation rate of Ghana using the inflation rate series from 1991 M01 to 2010 M12. The authors employed the Artificial Neural Network Model Approach, AR, and VAR models. The findings of the study revealed that the out-of-sample forecast from the Artificial Neural Network Model Approach yielded lower residuals compared to other techniques.

Other studies that modelled inflation rate in other continents using ARIMA models include, Ngailo *et al*, 2014; Duncan & Martínez García, 2018; Islam, 2018; Molebatsi & Raboloko, 2016; Udom & Phumchusri, 2014; Banerjee, 2017; Kabukcuoglu & Martnez-Garca, 2018; Iftikhar & Iftikharul-amin, 2013, and Pincheira & Gatty, 2016.

Most of the cited literature based on their model selection on either the model with the lowest AIC value, the SIC value, or the forecast accuracy measures (RMSE, MAPE, MSE, ME, etc.). This present study fit different ARMA, ARIMA, SARMA, and SARIMA models to the past and current inflation rates in Nigeria and selected the best models for forecasting the future occurrence of Inflation rate using the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Volatility, Convergence rate, Forecast Accuracy Measures such as Root Mean Square Error (RMSE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Mean Error (ME), and the Percentage of significant coefficients of the model.

2. Material and Methods

The data utilized in this study are the Nigeria monthly all-items (Year on Change) Inflation rate series obtained from the Nigeria Central Bank Databank (https://www.cbn.gov.ng/rates/inflrates.asp). These series spanned the period from January 2003 to October 2020. The data were analyzed using Eviews 10 and R Studio version 4.0 Software. We present the methods applied as follows,

Unit Root Test

In modeling time-series datasets, it is important to check for the stationarity of the series especially when fitting models like ARIMA, SARIMA, etc. The Augmented Dickey-Fuller (ADF) test was adopted for this study to ascertain the stationarity of the series.

The ADF test

We consider the traditional Augmented Dickey-Fuller (ADF) test regression given as,

$$\Delta Inf_t = \alpha + \beta t + (\theta - 1)Inf_{t-1} + \sum_{i=1}^{q} d_i \Delta Inf_{t-i} + \varepsilon_t \quad (1)$$

where Inf_t represents the inflation rate of Nigeria at a given time t. ε_t represents the error term. θ represents the parameter of the slope about the first lagged explanatory variable. Inf_{t-1} is 1, whenever there are characteristics of a unit root present in the series. q and d are the lag length and the slope associated with the augmentation component, respectively. The null hypothesis H_0: $\theta - 1 = 0$ is tested against the alternative hypothesis H_1: $\theta \leq 1$.

Autoregressive (AR) Model

The autoregressive process of order p is defined as,

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + e_t \quad (2)$$

where $\varphi_1, \ldots, \varphi_p$ are autoregressive parameters measuring the effect of individual $X_1, \ldots, X_{t-p}$ on X_p. It is "autoregressive" in the sense that it regresses over itself, with only lag differences. It is abbreviated as AR (p) process.

The stationarity condition of the AR (p) process is established thus,

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + e_t$$

$$\Rightarrow \; X_t = \varphi_1 B X_t + \varphi_2 B^2 X_t + \cdots + \varphi_p B^p X_t + e_t \quad (3)$$

By using the backward shift operator, $B^p X_t = X_{t-p}$, then,

$$X_t - \varphi_1 B X_t - \varphi_2 B^2 X_t - \cdots - \varphi_p B^p X_{t-p} = e_t$$

$$(1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p) X_t = e_t$$

Moving Average (MA) Model

The Moving Average process of order q [MA (q)] is defined as,

$$X_t = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} \quad (4)$$

where e_t is the white noise process with $e_t \sim N(0, \sigma^2)$. The MA (q) process is the finite approximation to the General Linear Process (G.L.P). In the MA (q) process, the process is stationary in structure, thus, there is the need to establish its invertibility condition.

From (4), we can easily write,

$$X_t = \ddot{\Theta}(B) e_t \quad (5)$$

$$\Rightarrow \quad e_t = \ddot{\Theta}^{-1}(B) X_t$$

where $\ddot{\Theta}^{-1}(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ exists.

This further simplifies as,

$$\ddot{\Theta}^{-1}(B) = (1 - H_1 B)(1 - H_2 B) \ldots (1 - H_q B) \quad (6)$$

Therefore, for invertibility, $\ddot{\Theta}^{-1}(B)$ must change and for convergence$|H_1 < 1|, |H_2 < 1|, \dots, |H_q < 1|$. Hence, for invertibility, all the root of the characteristic equation in (6) must lie outside the unit circle.

Autoregressive Moving Average (ARMA) Model

If both AR(p) and MA(q) components are present in a time series process, there is an autoregressive moving average, ARMA(p, q), process, satisfying,

$$X_t - \varphi_1 X_{t-1} - \varphi_2 X_{t-2} - \cdots - \varphi_p X_{t-p} = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \quad (7)$$

In compact form, this is,

$$\Phi(B) X_t = \ddot{\Theta}(B) e_t \quad (8)$$

Where $\Phi(B)$ *and* $\ddot{\Theta}(B)$ give the set of autoregressive and moving average parameters, and e_t is the white noise process.

To investigate the stationarity of the ARMA (p, q) process, all the roots of $\Phi(B)$, the characteristic equation must lie outside the unit circle. For invertibility, all the roots of $\ddot{\Theta}(B) = 0$ must also lie outside the unit circle.

Difference Operator (D)

The difference operator Δ is defined as:

$$\Delta X_t = X_t + X_{t-1} = (1 - B) X_t \quad (9)$$

Where X_t is the inflation time series; ΔX_t is the differenced inflation series; B is the Backshift operator defined as;

$$B = \frac{X_{t-1}}{X_t}$$

Generally, the kth difference order is given as

$$\Delta^k X_t = (1 - B)^k X_t \quad (10)$$

Autoregressive Integrated Moving Average (ARIMA) Model

This is a more general time series process in which leads to other lower variants of the AR or MA processes. It is the autoregressive integrated moving average process of order p, d, q, denoted as ARIMA(p, d, q). By generalizing the stationary ARMA(p, q) process in (7) for a case where one is not sure of the differencing order, one can specify,

$$(1-B)^d X_t - \varphi_1(1-B)^d X_{t-1} - \varphi_2(1-B)^d X_{t-1} - \cdots - \varphi_p(1-B)^d X_{t-p} = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \quad (11)$$

where in compact form,

$$\Phi(B)(1-B)^d X_t = \ddot{\Theta}(B) e_t \quad (12)$$

and $\Phi(B)\ and\ \ddot{\Theta}(B)$ are as defined earlier in the case of the ARMA process. The operator $(1-B)^d$ is the differencing operator, defined such that for d = 0, the entire process in (11 or 12) becomes the ARMA(p, q) process in (7).

For d = 1, the process in (11) becomes the ARIMA (p, 1, q) process,

$$(1-B)X_t - \varphi_1(1-B)X_{t-1} - \varphi_2(1-B)X_{t-1} - \cdots - \varphi_p(1-B)X_{t-p} = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \quad (13)$$

Where the backward shift operator B operates as $B^k X_t = X_{t-k}$. The difference between ARMA (p, q) and ARIMA (p, 1, q) processes is the first series differences (d =1) on the original time series, X_t.

Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

The Seasonal Autoregressive Integrated Moving Average (SARIMA) process is specified as,

$$\Phi_P(B^S)\vartheta_p(B)(1-B)^d(1-B^S)^D X_t = \emptyset_q(B)\ddot{\Theta}_Q(B^S) e_t \quad (14)$$

where d is the difference order, $\vartheta_p(B)$ and $\emptyset_q(B)$ are the autoregressive and moving average polynomials, respectively, defined as,

$$\vartheta_p(B) = 1 - \theta_1(B) - \theta_2(B^2) - \cdots - \theta_p(B^p),$$

$$\emptyset_q(B) = 1 - \varphi_1(B) - \varphi_2(B^2) - \cdots - \varphi_p(B^p),$$

and $\Phi_P(B^s)$ and $\ddot{\Theta}_Q(B^s)$ are the seasonal autoregressive and moving average polynomials, respectively defined as,

$$\Phi_p(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \cdots - \Phi_p B^{ps},$$

$$\ddot{\Theta}_q(B^s) = 1 - \ddot{\Theta}_1 B^s - \ddot{\Theta}_2 B^{2s} - \cdots - \ddot{\Theta}_q B^{qs},$$

The residual e_t is a white noise process. In notation form, one can write (14) as, ARIMA(p,d,q) x (P,D,Q)s where p is the autoregressive, d is the differencing, and q is moving average orders in the non-seasonal part of the model, respectively. Also P is the autoregressive, D is the differencing, and Q is the moving average orders in the seasonal part of the model, respectively (see Yaya and Fashae, 2014).

With d = D = 1, the model becomes the seasonal ARIMA(p, 1, q) x (P, 1, Q)s process,

$$\Phi_p(B^s)\vartheta_p(B)(1 - B)(1 - B^s)X_t = \emptyset_q(B)\ddot{\Theta}_q(B^s)e_t$$

With d = D = 0, the model becomes the seasonal ARMA(p, q) x (P, Q)s process,

$$\Phi_p(B^s)\vartheta_p(B)X_t = \emptyset_q(B)\ddot{\Theta}_q(B^s)e_t$$

3. Results and Discussion

Figure 1 shows the time plot of the original series and the first differenced plot. We observed that there is a fluctuating movement in Nigeria's inflation rate over the years considered. The graph shows that there is a sharp upward movement in the inflation rate from March 2003 till February 2004 where the inflation rate sharply dropped till February 2005. The rate increases sharply and reached its peak in August 2005. The rate dropped sharply afterward, and the lowest inflation rate was recorded in July 2006. The inflation rates fluctuate thereafter, showing upward and downward movements over time. There is evidence of trend stationarity

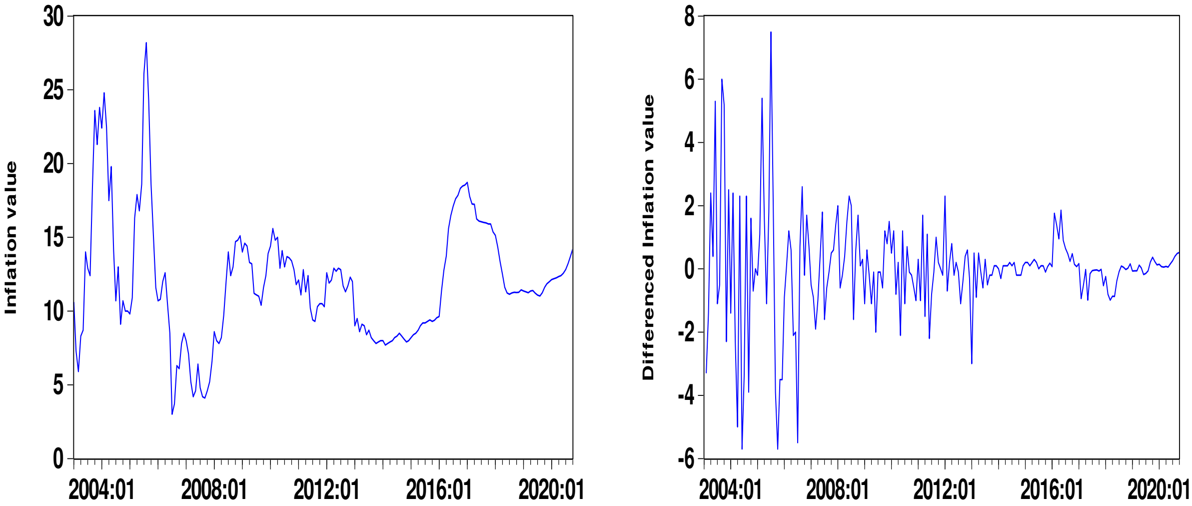


Figure 1: *Time Plots of original series and first difference series of Nigeria Inflation Rate (2003M1 to 2020M10)*

in the original series. However, inflation rates appear to be trend stationary. The first differenced series appears to be stationary.

Table 1: Descriptive Statistics

Statistic	Inflation Rates
Mean	11.99304
Median	11.52000
Maximum	28.20000
Minimum	3.000000
Std. Dev.	4.220357
Skewness	0.896277
Kurtosis	4.556285
Observations	214

Source: Extracted from EViews result output

As presented in Table 1 above, the inflation rate has a mean value of 11.99. The highest inflation rate recorded during the period of study was 28.2, showing a huge difference from the rate (72.8%) recorded in 1995 as reported by Nyoni et al. (2018). The skewness value of 0.896 indicates that the rate is slightly positively skewed. The kurtosis value of 4.556 indicates that the inflation series deviate a little from normality. Table 2 shows the result of the ADF test on the original inflation series and first differenced inflation series. As displayed in the table, three regression equations (No constant and trend, with constant only, and with constant and trend) were considered. The Table 2 shows the test statistic and p-value (in parenthesis) of each test. Also, the critical values for the three significant levels (1%, 5%, and 10%) were displayed. The results show that when the regression equation does not contain a

Table 2: Results of the ADF unit root test

	Test critical values	None	Intercept	Intercept and Trend
Inflation Rate		-0.864792 (0.340)	**-3.526344 (0.008)**	**-3.531104 (0.039)**
	1% level	-2.575916	-3.461178	-4.001931
	5% level	-1.942331	-2.874997	-3.431163
	10% level	-1.615703	-2.574019	-3.139232
D (Inflation Rate)		**-12.45552 (0.000)**	**-12.43017 (0.000)**	**-12.40124 (0.000)**
	1% level	-2.575916	-3.461178	-4.001931
	5% level	-1.942331	-2.874997	-3.431163
	10% level	-1.615703	-2.574019	-3.139232

Bolded figures indicate significant at 5%

constant and trend, the original series contains a unit root (not stationary); however, the differenced series is stationary at all significant levels. When the regression equation contains a constant and a constant and trend, the original series, as well as the differenced series are stationary for both cases.

Model Identification

We estimated 169 ARMA, 169 ARIMA, 1521 SARMA, and 1521 SARIMA models using the Automatic ARIMA Forecasting function in Eviews 10 to identify the most appropriate model for modelling inflation rate in Nigeria. The top 12 models from each result were displayed below. We selected the best model based on the model with the lowest Akaike Information Criterion (AIC) value, volatility Sigma Square value, and convergence rate. We then used the R studio software for model diagnostic and forecasting.

As presented in Table 3, the model with the lowest AIC value and least volatility, SARMA (3, 3) x $(1, 2)_{12}$ model appears as the best model by considering only its AIC value and volatility. However, the model failed to improve objectives and the volatility (sigma square)

Table 3: Determination of the optimal model for inflation rate series

ARMA Models				ARIMA Models			
Model	**AIC**	**σ^2**	**LogL**	**Model**	**AIC**	**σ^2**	**LogL**
(0, 11)	3.5521	1.6615	-367.075	(12, 1, 11)	3.5270	1.4487	-350.6271
(11, 12)	3.5547	1.4088	-355.3603	(12, 1, 10)	3.5479	1.4572	-353.8562
(1, 11)	3.5556	1.6607	-366.4512	(12, 1, 7)	3.5522	1.5918**	-357.3133
(0, 12)	3.5563	1.6594	-366.5263	(12, 1, 8)	3.5535	1.5549	-356.4454
(2, 12)	3.5570	1.6085	-364.6029	(12, 1, 9)	3.5661	1.4992	-356.7959
(1, 12)	3.5580	1.6290	-365.7122	(11, 1, 12)	3.5685	1.4445	-355.0495

(9, 11)	3.5598	1.4831	-358.8958	(0, 1, 12)	3.5690	1.6689	-366.1752
(10, 12)	3.5616	1.4781	-357.0934	(1, 1, 12)	3.5723	1.6684	-365.4534
(11, 11)	3.5625	1.4773	-357.1909	(7, 1, 12)	3.5752	1.5216	-359.7574
(7, 12)	3.5636	1.5112	-360.3045	(9, 1, 12)	3.5767	1.5135	-357.9158
(3, 12)	3.5640	1.6126	-364.3538	(8, 1, 12)	3.5794*	1.5728	-359.2092
(8, 11)	3.6032	1.8063	-373.5400	(6, 1, 12)	3.5757	1.5615	-360.8163
SARMA Models				**SARIMA Models**			
Model	**AIC**	**σ^2**	**LogL**	**Model**	**AIC**	**σ^2**	**LogL**
(3, 3)(1, 2)	**3.3992**	**1.4109**	**-352.7126**	(3, 1, 4)(1, 1, 2)	3.4243	1.4219	-352.6871
(3, 4)(1, 2)	3.4084	1.4110	-352.7020	(2, 1, 4)(1, 1, 2)	3.4306	1.4648	-354.3569
(3, 3)(0, 2)	3.4070	1.4385	-354.5479	(4, 1, 5)(0, 1, 2)	3.4315	1.4139	-352.4605
(3, 3)(2, 2)	3.4079	1.3315	-352.6477	(3, 1, 4)(2, 1, 1)	3.4335	1.4640	-353.6649
(3, 3)(2, 1)	3.4094	1.4541	-353.8085	(3, 1, 4)(0, 1, 2)	3.4337	1.4548	-354.6936
(7, 4)(0, 2)	3.4118	1.3783	-350.0657	(2, 1, 3)(2, 1, 1)	3.4338	1.5163	-355.7015
(4, 2)(2, 1)	3.4130	1.4562	-354.1949	(2, 1, 3)(0, 1, 2)	3.4366	1.5124	-356.9991
(4, 3)(2, 1)	3.4186	1.4535	-353.7975	(4, 1, 4)(1, 1, 2)	3.4529	1.2290	-354.7339
(3, 4)(2, 1)	3.4187	1.4537	-353.8081	(2, 1, 3)(1, 1, 1)	3.460	1.5577	-359.5389
(3, 0)(1, 2)	**3.4647**	**1.5603****	**-362.7236**	**(2, 1, 3)(1, 1, 2)**	**3.4756**	**1.5616****	**-360.1505**
(3, 1)(0, 2)	**3.4953**	**1.6371****	**-366.0018**	(2, 1, 3)(0, 1, 1)	3.5272	1.7115	-367.6525
(3, 2)(2, 1)	**3.4962**	**1.6305****	**-364.0994**	(3, 1, 3)(1, 1, 1)	3.5340	1.6468	-366.3718

** indicates a significant Sigma Square (volatility) at 5%; ** indicates significant volatility and a convergence model; bolded figure denotes the models with the good convergence rate. In red denotes the model with the lowest AIC value and Volatility.*

is not significant. The failure of the model to improve objectives and the insignificance of its volatility are likely to influence the forecast ability of the model. By considering the least convergence rate and the significance of the volatility, SARMA (3, 1) x $(0, 2)_{12}$ and SARMA (3, 2) x $(2, 1)_{12}$ appears as the best model. We conducted a seasonality and break point unit root test. The results show that a moving seasonality is present in the data and there is no break point unit root in the data. To ascertain and validate the best model, five models, SARMA (3, 3) x $(1, 2)_{12}$, SARMA (3, 0) x $(1, 2)_{12}$, SARMA (3, 1) x $(0, 2)_{12}$, SARMA (3, 2) x $(2, 1)_{12}$, and SARIMA (2, 1, 3) x (1, 1, 2) were further examined.

Model Parameter Estimation

Table 4a: *S***ARMA (3, 3) x $(1, 2)_{12}$ model**

Coefficients	Constant	θ_1 AR(1)	θ_2 AR(2)	θ_3 AR(3)	Φ_1 SAR(12)	φ_1 MA(1)	φ_2 MA(2)	φ_3 MA(3)	∂_1 SMA(12)	∂_2 SMA(24)
Estimate	**11.7106**	**-0.3486**	**0.2402**	**0.8576**	**-0.5293**	1.5199	1.3948	0.33325	-0.0064	**-0.7200**
Standard Error	0.5499	0.0364	0.0358	0.0314	0.1365	8.5536	17.1846	4.8318	0.1954	0.1063
P-value	0.0000	0.0000	0.0000	0.0000	0.0001	0.8591	0.9354	0.9452	0.9739	0.0000
σ_ε^2 = 1.4109	log *lik = -352.7126* *AIC = 3.3992,* *SIC = 3.5722,* *adjusted R^2= 0.9165,* *Convergence = Failure to improve objective after 201 iterations*									

Bolded figures indicate significant at 1% significance level.

Model:

$$Inf_t = 11.71 - 0.35BInf_t + 0.24B^2Inf_t + 0.86B^3Inf_t + 1.52Be_t + 1.39B^2e_t + 0.33B^3e_t + 0.53B^{12}Inf_t - 0.01B^{12}e_t - 0.72B^{24}e_t + 0.18B^{13}x_t - 0.13B^{14}Inf_t - 0.45B^{15}Inf_t - 0.01B^{13}e_t - 0.01B^{14}e_t - 0.002B^{14}e_t - 1.09B^{25}e_t - B^{26}e_t - 0.24B^{27}e_t$$

Table 4b: *S*ARMA (3, 0) x (1, 2)$_{12}$ model

Coefficient	Constant	θ_1 AR(1)	θ_2 AR(2)	θ_3 AR(3)	Φ_1 SAR(12)	∂_1 SMA(12)	∂_2 SMA(24)
Estimate	**11.7154**	**1.0879**	-0.0841	-0.0662	**-0.6556**	0.0561	**-0.8078**
Standard Error	0.5198	0.0441	0.0727	0.0493	0.1123	0.2233	0.1382
P-value	0.0000	0.0000	0.2488	0.1807	0.0000	0.8020	0.0000
σ_ε^2 = **1.5603**	log *lik = -362.7236, AIC = 3.4647, SIC = 3.5905, adjusted* R^2*= 0.909, Convergence = 46 iterations*						

Bolded figures indicats significant at 1% significance level.

Model:

$$Inf_t = 11.71 + 1.09BInf_t - 0.08B^2Inf_t - 0.07B^3Inf_t - 0.65B^{12}Inf_t + 0.06B^{12}e_t - 0.81B^{24}e_t + 0.71B^{13}Inf_t - 0.05Inf_t - 0.04B^{15}Inf_t$$

Table 4c: *S*ARMA (3, 1) x (0, 2)$_{12}$ model

Estimate	Constant	θ_1 AR(1)	θ_2 AR(2)	θ_3 AR(3)	φ_1 MA(1)	∂_1 SMA(12)	∂_2 SMA(24)
Coefficient	**11.6950**	**1.3569**	-0.3724	-0.0374	-0.2848	**-0.6023**	**-0.2947**
Standard Error	0.4766	0.4894	0.5423	0.0939	0.4909	0.1363	0.0787
P-value	0.0000	0.0061	0.4931	0.6910	0.5624	0.0000	0.0002
σ_ε^2 = **1.6371**	log *lik = -366.0018, AIC = 3.4953, SIC = 3.6212, adjusted* R^2*= 0.9045, Convergence = 29 iterations*						

Bolded figure indicates significant at 1% significance level.

Model:

$$Inf_t = 11.69 + 1.36BInf_t - 0.37B^2Inf_t - 0.04B^3Inf_t - 0.28Be_t - 0.60B^{12}e_t - 0.29B^{24}e_t + 0.17B^{13}e_t + 0.08B^{25}e_t$$

Table 4d: *S*ARMA (3, 2) x (2, 1)$_{12}$ model

Coefficients	Constant	θ_1 AR(1)	θ_2 AR(2)	θ_3 AR(3)	Φ_1 SAR(12)	Φ_2 SAR(24)	φ_1 MA(1)	φ_2 MA(2)	∂_1 SMA(12)
Estimate	**11.7081**	1.1519	-0.3800	0.1574	0.1480	**-0.2574**	-0.0641	0.2619	**-0.7893**
Standard Error	0.5595	0.6353	0.9859	0.4441	0.0954	0.0698	0.6133	0.3738	0.1250
P-value	0.0000	0.0713	0.7003	0.7234	0.1222	0.0003	0.9169	0.4844	0.0000
σ_ε^2 = **1.6305**	log *lik = -364.0994, AIC = 3.4962, SIC = 3.6535, adjusted* R^2*= 0.904, Convergence = 31 iterations*								

Bolded figures indicate significant at 1% significance level.

Model:

$$Inf_t = 11.71 + 1.15BInf_t - 0.38B^2Inf_t + 0.16B^3Inf_t - 0.06Be_t + 0.26B^2e_t + 0.15B^{12}Inf_t - 0.26B^{24}Inf_t - 0.79B^{12}e_t + 0.17B^{13}Inf_t - 0.06B^{14}Inf_t - 0.02B^{15}Inf_t + 0.30B^{25}Inf_t - 0.10B^{26}Inf_t - 0.04B^{27}Inf_t - 0.05B^{13}e_t - 0.21B^{14}e_t$$

Table 4e: SARIMA (2, 1, 3) x (1, 1, 2)$_{12}$ model

Coefficients	Constant	θ_1 AR(1)	θ_2 AR(2)	Φ_1 SAR(12)	φ_1 MA(1)	φ_2 MA(2)	φ_3 MA(3)	∂_1 SMA(12)	∂_2 SMA(24)
Estimate	0.0050	**-1.2903**	**-0.7029**	**-0.6919**	**1.4611**	**1.0274**	**0.2670**	0.0680	**-0.8066**
Standard Error	0.0459	01181	0.1104	0.1252	0.1268	0.1355	0.0438	0.2454	0.1549
P-value	0.9139	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.7819	0.0000
σ_ε^2 = **1.5616**	log *lik = -360.1505 AIC = 3.4756, SIC = 3.6334, adjusted* R^2*= 0.3883, Convergence = 71 iterations*								

Bolded figures indicate significant at 1% significance level.

Model:

$$\begin{aligned}\Delta Inf_t = 0.005 - 1.295B\Delta Inf_t - 0.70B^2\Delta Inf_t + 1.46Be_t + 1.03B^2e_t + 0.26B^3e_t - 0.69B^{12}\Delta Inf_t \\ + 0.07B^{12}e_t - 0.81B^{24}e_t - 0.89B^{13}\Delta Inf_t - 0.49B^{14}\Delta Inf_t + 0.10B^{13}e_t + 0.07B^{14}e_t \\ + 0.02B^{14}e_t - 1.18B^{25}e_t - 0.83B^{26}e_t - 0.22B^{27}e_t\end{aligned}$$

A positive and significant AR component implies that past inflation rates in Nigeria play significant roles in explaining the current inflation rates. The positive and significant MA component is an indication that immediate past shocks to inflation in Nigeria significantly explains the current inflation rates. The models were subjected to the diagnostic test.

Table 5: Models Residuals Check

Model	Ljung-Box test	Normality	Lags outside 95% bounds
SARMA (3, 2)(2, 1)	42.492 (0.2116)	Right tailed	22
SARMA (3, 1)(0, 2)	43.374 (0.1858)	Right tailed	9, 21
SARMA (3, 3)(1, 2)	40.074 (0.2942)	Normally Distributed	11, 17
SARMA (3, 0)(1, 2)	40.891 (0.2644)	Right tailed	21
SARIMA (2, 1, 3)(1, 1, 2)	43.371 (0.1859)	Normally Distributed	10, 11,

Output of the tests are not reported here but can be provided by the authors upon request

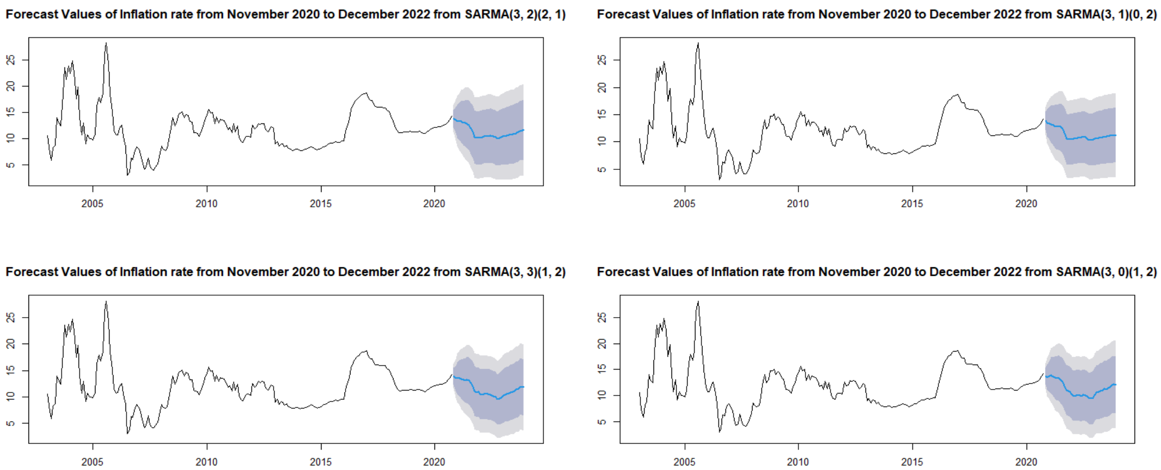
Table 5 presents the autocorrelation and normality check results. We present the test statistics for Ljung-Box and its p-value (in parenthesis) and the lags that fall outside the 95% bounds. The results show that one or two lags from each model fall out of the 95% bounds. The lags that fall out of the bands are probably due to chance since we are likely to expect one or two out of 27 sample autocorrelations to exceed the significant bounds. Also, the Ljung-Box p-value for all 5 models exceeded 0.05. These results indicate that there is little evidence for non-zero autocorrelations in the model's forecast errors. However, the normality check shows that the residuals generated from SARMA (3, 3) x (1, 2)$_{12}$ and SARIMA (2, 1, 3) x (1, 1, 2)$_{12}$ are normally distributed while others the residuals from other model are not. We further investigate the forecast accuracy measures of the models. The results presented in Table 6

Table 6: Accuracy measures

Models	RMSE	MPE	MAPE	MAE	ME	Adjusted R^2	AIC	SIC	Volatility	% of Sig. coefficient.
SARMA(3, 2)(2, 1)	1.2769	-0.9053	8.2908	0.8577	0.0352	0.904	3.4962	3.6535	1.6305	33%
SARMA(3, 1)(0, 2)	1.2845	-0.8759	8.0968	0.8626	0.0272	0.904	3.4953	3.6212	1.6371	57%
SARMA(3, 3)(1, 2)	**1.1878**	-0.7693	**7.8247**	**0.8274**	0.0277	**0.916**	**3.3992**	**3.5722**	**1.4109**	60%
SARMA (3, 0)(1, 2)	1.2491	-0.8061	8.1103	0.8549	0.0312	0.909	3.4647	3.5905	1.5603	57%
SARIMA (2, 1, 3) (1, 1, 2)	1.2901	**-0.5306**	8.2396	0.8615	**0.0161**	0.388	3.4756	3.6334	1.5616	**78%**

Bolded figures indicate the best forecast accuracy values

show that SARMA (3, 3) x $(1, 2)_{12}$ model performs in terms of volatility, parsimony (SIC), AIC value, the goodness of fit, and forecast accuracy measures such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE). SARIMA (2, 1, 3) x (1, 1, 2) model appears as the best in terms of the percentage of significant coefficients, and forecast accuracy such as Mean Percentage Error (MPE) and Mean Error. Based on the result presented in table 5, SARMA (3, 3) x $(1, 2)_{12}$ model was selected as the best model for forecasting the monthly inflation rate in Nigeria. This finding closely conforms to the findings of Otu *et al.,* (2014). The authors found that the SARIMA model is the appropriate model for forecasting inflation rate in Nigeria. The model was used to make a forecast for November 2020 to December 2023**.** Figure 2 shows the graphs of the forecast values of the 5 models. The forecast values using the selected model presented in Table 7 shows that the inflation rate in Nigeria is projected to be 13.48%,



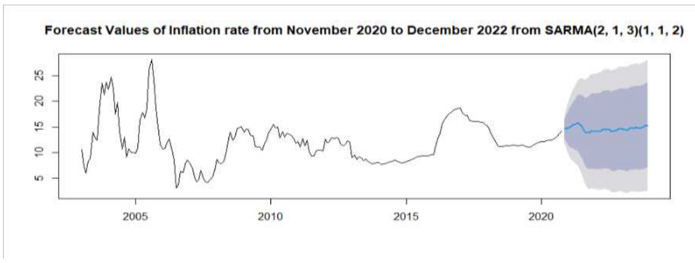


Figure 2: *Plot of Forecast values of the five models*

Table 7: Nigeria Inflation rate Forecast Values (Nov 2020 – Dec 2023)

	Jan	Feb	Mar	April	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2020											13.96	13.48
2021	13.58	13.59	13.41	13.27	13.14	13.20	13.04	12.61	12.03	11.15	10.84	10.97
2022	10.61	10.47	10.62	10.51	10.54	10.40	10.32	10.19	9.98	9.51	9.64	9.82
2023	10.10	10.41	10.48	10.63	10.82	10.97	11.11	11.34	11.49	11.84	11.88	11.81

10.98%, 9.82%, and 11.81% by the end of 2020, 2021, 2022, and 2023 respectively. The forecasted figures are an indication that the inflation rates are likely to continue to decrease for the next two years, but likely to rise again in 2023.

4. Conclusion

One of the factors that contribute to the economic growth of a country is the stability of the prices of goods and services. Ensuring price stability in the country should be the major focus and objective of the monetary policymakers. This study aimed to provide a foresight of the likely future inflation rate to the policymakers in Nigeria by modelling and forecasting the inflation rate in Nigeria. The study examined several ARMA, ARIMA, SARMA, and SARIMA models. Based on the AIC and SIC values, Volatility, and forecast accuracy measures, SARMA (3, 3) x $(1, 2)_{12}$ model appears as the best and most appropriate model for forecasting the monthly inflation rate in Nigeria. The model was used to make a forecast of Nigeria's monthly inflation rates from November 2020 to December 2023.

Based on the forecast values, we recommend that appropriate monetary management should be adopted by the Central Bank of Nigeria to address inflation in the country via a stable monetary growth rate rules. Also, policies such as deregulation and privatization should be put into consideration by the policymakers in Nigeria to improve long term productivity, competitiveness as well as innovation in Nigeria as it would further minimize the inflation rate.

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