Modeling Seasonal Autoregressive Integrated Moving Average on Forecasting of Inflation Rates in Nigeria

I. Ahmed[1*]; B. Maijamaa[1]; Y. Musa[1]; and O.P. Adebayo[2]

[1]Department of Statistics, Nasarawa State University Keffi, Nasarawa State, Nigeria.
[2]Department of Statistics, Phoenix University Agwada, Nasarawa State, Nigeria.

E-mail: ibrahimloko@nsuk.edu.ng*
omolade.onifade@yabatech.edu.ng

Telephone: +2348033627847 *
+2349019964334

ABSTRACT

Emerging economies such as Nigeria place great importance on economic stability for sustained growth and development. Understanding and accurately modeling and forecasting inflation rates are crucial in this regard. Price stability is a key objective for every government and serves as a significant economic indicator. It is often used as a basis for discussions on the state of the economy by governments, politicians, economists, and other stakeholders (Suleman, *et al*., 2012).

The objective of this study is to utilize seasonal autoregressive integrated moving averages to forecast inflation rates in Nigeria. Specific aims include identifying patterns in Nigerian inflation data (such as stationarity/non-stationarity and seasonality), determining the best SARIMA model for the Nigerian inflation rate data, and forecasting future monthly inflation using the best-estimated SARIMA model. In the study focused on modeling and forecasting inflation rates in Nigeria, the researchers utilized the seasonal autoregressive integrated moving average (SARIMA) model. Data on Nigeria's inflation rates from 1996 to 2020 was obtained from the Central Bank of Nigeria (CBN) data portal.

The analysis was conducted using R-Software (version 3.4.0). The average inflation rate in Nigeria was found to be 12.454 during the study period. Notably, there was an early decline in inflation in Nigeria observed from 1996 to 2000. The Augmented Dickey-Fuller (ADF) test indicated that the inflation series is stationary (D= -5.3636, P<0.05). After considering the minimum values of AIC and BIC, the SARIMA (2,0,1)(2,0,1)[12] model was identified as the most suitable for fitting Nigeria's inflation rates. The forecast suggests that the inflation rate will average 12.50% from January 2023 to December 2025. Subsequently, it is projected to increase to an average of 13.0% from July 2026 to July 2027 and then decrease to an average of 12.692% from August 2027 to December 2030. Among other recommendations, it is advised that the Nigerian government and regulatory agencies implement policies to manage the predicted pattern of inflation in the country

(Keywords: SARIMA, Augmented Dickey-Fuller, ADF, Autoregressive Moving Average Process, ARIMA)

INTRODUCTION

Inflation is the persistent increase in consumer prices or the decline in the purchasing power of money caused by an increase in available currency and credit beyond the proportion of available goods and services in a particular country. It is the rate at which the general level of prices for goods and services is rising, leading to falling purchasing power of currency. Central banks strive to reduce inflation to maintain a stable economy (Osuolale, 2017).

Recognizing the detrimental impacts of inflation on the economy, world-leading central banks have aligned on the chief goal of monetary policy - to control inflation. High inflation and interest rates hinder economic growth by discouraging investment and reducing a country's productivity. In most countries, the nominal interest rate is the key instrument for achieving the inflation target. Therefore, inflation affects all facets of life and all economic entities.

Various factors have a significant impact on the stability of an economy, ranging from microeconomic to macroeconomic factors. It is essential for all stakeholders, including the common man, policymakers, and government agencies, to recognize their crucial roles in maintaining economic stability. The direct and indirect effects of macroeconomic variables play a pivotal role in stabilizing the economy by dealing with aggregate levels rather than individual units.

One of the most critical macroeconomic variables that influence economic stability is inflation, which poses a substantial threat to economies globally, regardless of their development status. Even economies like Brazil, Venezuela, India, Pakistan, Germany, Israel, Bolivia, and Zimbabwe, despite implementing stringent measures to mitigate its impact, continue to face adverse effects from inflation (Osuolale, 2017). This underscores the necessity of constant forecasting to empower policymakers in proactively addressing the dynamic nature of inflation (Suleman and Sarpong, 2012).

The government of any nation is entrusted with the crucial task of safeguarding its plans and programs from being derailed by unpredictable and soaring prices. It is imperative for every firm to operate within a stable macroeconomic environment that is resilient to abrupt price changes, as such fluctuations can severely hamper accurate forecasting and strategic planning. Additionally, individuals seek to shield themselves from the adverse impacts of unforeseen price hikes. This underscores the vital importance of conducting a comprehensive study of inflation on a monthly basis in order to establish an enduring and dependable model of its trends (Taiwo, 2011).

Sloman and Kevin (2007) expound that inflation can manifest as either demand-pull inflation or cost-push inflation. Demand-pull inflation arises from a sustained surge in aggregate demand, prompting firms to increase prices and, to some extent, ramp up production. Conversely, cost-push inflation is linked to continuous escalations in production costs experienced by firms. Consequently, firms respond by raising prices, passing the costs on to consumers, and, to some degree, scaling back production (Hendry, 2006).
Tucker (2007) highlights the existence of multiple measures of inflation, attributable to the presence of various price indices across different economic sectors. Two widely recognized indices used to report inflation rates in many countries are the Consumer Price Index (CPI), which gauges prices affecting typical consumers, and the Gross Domestic Product (GDP) deflator, which measures prices of locally produced goods and services. Hence this study aims to conduct a time series modeling and forecasting the future inflation rate in the country. This will be a great relevance to the central banks in its attempt to limit inflation rate and improve the economy of the country.

EMPIRICAL REVIEW

The study by Osuolale, *et al.* (2017) offers valuable insights into modeling and forecasting the inflation rate in Nigeria. Through rigorous analysis of inflation rate data from January 2006 to December 2015, employing advanced statistical methodologies, the study has revealed compelling findings. The identified model for the inflation rate, supported by robust parameter confirmation and extensive statistical testing, provides a comprehensive understanding of the inflation trends in Nigeria. With a meticulous comparison of various model options, the study determines the best-fit model as ARIMA (0,1,1), enhancing the accuracy of inflation rate forecasts for the next 36 months. These findings underscore the significance of the study in enabling informed decision-making and strategic planning in the context of Nigeria's economic landscape.

Nse and Anietie (2018) undertook a comprehensive study on a Predictive Model for Inflation in Nigeria, analyzing quarterly data from 1995 to 2016. Four dynamic models were evaluated: level lagged variables, differenced lagged variables, log-transformed lagged variables, and differenced log-transformed lagged variables. The selection of the best predictive model was based on the Schwarz Information Criterion (SIC) value. Their empirical findings revealed that the level from models outperformed the different form models. Therefore, the level-lagged model was chosen as the preferred model for its simplicity and accuracy. Moreover, the model's predictions demonstrated stability, with actual interest rate values falling well within the computed 95% prediction interval. Ultimately, the study concludes that previous values of interest rate and money supply play a significant role in predicting future inflation rates in Nigeria.

In their 2019 study, Olatayo and Taiwo conducted a Univariate Time Series Analysis of Nigeria's Monthly Inflation Rate. They examined the fluctuations and volatility in Nigeria's inflation rates using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. After identifying four potential models for Nigeria's inflation forecast, they validated SARIMA (1,1,1)(0,0,1)12 in the estimation stage using Akaike Information Criteria (AIC), Schwartz Bayesian Criteria (SBC), and Hannan-Quinn Criteria (HQC) parameters. The diagnosed model results indicated that it was adequate and parsimonious. Consequently, the model was fitted to obtain monthly forecast values with minimal root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) parameters, respectively. In conclusion, the model was a good fit with minimal parameters, and the generated forecast revealed high fluctuation and volatility in Nigeria's inflation rates.

METHODOLOGY

The dataset used for this study was obtained from the Central Bank of Nigeria (CBN) data portal. It includes the monthly inflation rate in Nigeria from 1996 to 2020, covering a span of 25 years. The research uses the documentary method for data (secondary data) collection, involving gathering data from the files and records of an organization.

Method of Data Analysis and Model Specification

A seasonal ARIMA model of the form $SARIMA(p, d, q) \times (P, D, Q)_{[m]}$ was fitted for the Nigerian inflation rate data.

Where;

p = order of the non-seasonal AR component
q = order of the non-seasonal MA component
d = non-seasonal difference
P = order of the seasonal AR component
Q = order of the seasonal MA component
D = seasonal difference

The model is given by:

$$(1-B)^d(1-B)^D\varphi(B)\Phi(B)X_t = \theta(B)\Theta(B)\varepsilon_t \quad \textbf{(1)}$$

We set $m = 12$ since the inflation rate series is made of monthly observations. Thus:

$$(1-B)^d(1-B)^D\varphi(B)\Phi(B)X_t = \theta(B)\Theta(B)\varepsilon_t \quad \textbf{(2)}$$

X_t is the time series value at time t.

φ_i *θ, Φ* and *Θ*, are polynomials of the order *p*, *q*, *P*, and *Q*, respectively.

B is the backward shift operator and the white noise process is denoted by ε_t

ACF/PACF Plots

In an AR or MA model, the seasonal component is indicated by the seasonally lagged partial autocorrelation function (PACF) and autocorrelation function (ACF) plots. For instance, an ARIMA (0, 0, 0) (0, 0, 1)12 model will exhibit a spike at lag 12 in the ACF, with no other significant spikes. The PACF will demonstrate exponential decay at lags 12, 24, 36, and so on. Similarly, an ARIMA (0, 0, 0) (1, 0, 0)12 model will display exponential decay at the seasonal lags in the ACF, and only one significant spike at lag 12 in the PACF. When determining the appropriate seasonal orders for an ARIMA model, it is crucial to focus on the seasonal lags. The modeling process is quite similar to that for non-seasonal data, except for the necessity of selecting seasonal AR and MA terms in addition to the non-seasonal components of the model.

Autoregressive Moving Average Process (ARMA) or Mixed Process

According to Jeffrey (1990), sophisticated models may be necessary to capture autocorrelation patterns. The autoregressive moving-average model, or ARMA(p, q) model, combines the AR(p) and MA(q) models to provide a more comprehensive approach. Jeffrey elaborates that this model not only forecasts Y based on a linear combination of actual past values but also considers a linear combination of past errors. The general ARMA (p, q) model can be expressed as:

$$Y_i = \mu + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \cdots + \alpha_p Y_{t-p} + e_i - \theta_1 e_{i-1} - \theta_2 e_{i-2} - \cdots - \theta_q e_{i-q} \quad \textbf{(3)}$$

$$Y_i = \sum_{k=1}^{p} \alpha_k Y_{t-k} - \sum_{k=1}^{q} \theta_k e_{i-k} + \mu e_t\, \theta_2 \quad \textbf{(4)}$$

Just like the AR (p) model, the ARMA (p, q) also exhibits decreasing autocorrelation as the distance between residuals increases.

Autoregressive Integrated Moving Average Model (ARIMA)

Remember, the autoregressive component's order is represented by p, the order of differencing needed to achieve stationarity is represented by d, and the moving average component's order is represented by q. In general, the ARIMA process can be expressed as:

$$z_t = \sum_{k=1}^{p} \alpha_k Z_{t-k} - \sum_{k=1}^{q} \theta_k e_{t-k} + \mu + e_t \quad \textbf{(5)}$$

Seasonal Models

A time series that is purely seasonal only has seasonal AR or MA parameters. Seasonal autoregressive models are constructed using parameters known as seasonal autoregressive (SAR) parameters. These SAR parameters show the autoregressive connections that exist between time series data points that are spaced apart by multiples of the number of periods within each season. A general autoregressive model with p SAR parameters is expressed as: $Y_t = \sum_{i=1}^{p} \alpha_{is} Y_{t-is},$

Where:
Y_{t-is} is of order s, Y_{t-2s} is of order 2s and Y_{t-ps} is of order ps.

A model with one SAR parameter is written as:

$$Y_t = \alpha_s Y_{t-s} + e_t \quad \textbf{(6)}$$

Seasonal moving Average (SMA) models are built with seasonal moving average (SMA) parameters, and the general SMA model with Q parameters is given by:

$$Y_t = \sum_{i=1}^{Q} \theta_{is} e_{t-is} + e_t \quad \textbf{(7)}$$

The general mixed SAR and SMA model is given by:

$$Y_t = \sum_{i=1}^{p} \alpha_{is}\, Y_{t-is} + \sum_{i=1}^{Q} \theta_{is} e_{t-is} + e_t \quad \textbf{(8)}$$

The order of the seasonal ARMA process is given in terms of both Ps and Qs.

Seasonal Autoregressive Integrated Moving Average (SARIMA) Models

To effectively estimate the seasonal autoregressive integrated moving average (SARIMA) model for any variable, you need to navigate through four main steps: Identification, Estimation, Diagnostic checking, and Forecasting. The basic form of the SARIMA model is denoted by *SARIMA (p,d,q)×(P, D, Q)$_m$* and the model is given by:

$$B^m Z_t = B^m Z_{t-1}$$

$$\varphi_p(B)\Phi_p(B^m)\nabla^d \nabla_m^d Z_t = \theta_q(B)\Theta_Q(B^m)a_t \quad \textbf{(9)}$$

Where,

Z_t is the time series value at time *t* and φ, θ, Φ and Θ, are polynomials of the order *p*, *q, P*, and *Q,* respectively.

B is the backward shift operator,

$$B^m Z_t = B^m Z_{t-1}$$

and $\nabla = (1-B)$.

Order of seasonality is represented by *m*.

Non-seasonal and seasonal difference orders are denoted by d and D, respectively.

White noise process is denoted by a_t.

Modelling Procedure

The Box-Jenkins methodology has been employed to determine the optimal seasonal ARIMA model for the Nigerian inflation rate data. When implementing the Box-Jenkins method to fit an ARIMA model to a time series dataset, the following process serves as a valuable general approach:

a. Plot the data. Identify any unusual observations.

b. If necessary, transform the data (using a Box-Cox transformation) to stabilize the variance.

c. If the data are non-stationary: take the first differences of the data until the data are stationary.

d. Examine the ACF/PACF: Is an AR(pp) or MA(qq) model appropriate?

e. Try your chosen model(s), and use the AICc to search for a better model.

f. Check the residuals from your chosen model by plotting the ACF of the residuals, and doing multiple tests of the residuals. If they do not look like white noise, try a modified model.

g. Once the residuals look like white noise, calculate forecasts.

Model Selection Criteria

The AIC and BIC were considered in choosing the best model. Smaller values indicate a better model.

AIC: Akaike's Information Criterion (AIC) adjusts the 2-Log Likelihood by twice the number of parameters in the model. $AIC = -2L + 2N_p$

The -2 log-likelihood is the most basic measure for model selection and is given as:

$$L = -Nln(\sigma^2{}_a) - \frac{SSQ'}{2\sigma^2{}_a} - \frac{2Nln(2\pi)}{2}$$

BIC: The Bayesian information criterion (BIC) is a measure for selecting and comparing models based on the 2-log-likelihood. Smaller values indicate better models. The BIC also penalizes over-parametrized models, but more strictly than the AIC because the BIC accounts for the size of the dataset as well as the size of the model.

$$BIC = -2L + \ln(N)N_p$$

Where;

N = Total number of observations,

L= -2 log likelihood,

$\sigma^2{}_a$=variance of residuals

N_p= Number of parameters $\left(N_p = p + q + d + P + Q + D + m\right)$

SSQ = residuals sum of squares

DATA ANALYSIS AND RESULTS

Descriptive Statistics

Table 1 displays the descriptive statistics for Nigeria's inflation rates. The dataset includes 300 observations spanning 25 years. The average inflation rate for the period was 12.454. The coefficient of variation, at 50.26, indicates that the inflation rate has an approximate 50% variation. The mode (3.0), median (11.7), and mean (12.454) are not very close to each other, suggesting that the inflation rate data is not normally distributed.

Table 1: Descriptive Statistics of Inflation Data.

Descriptive Measures	Estimate
N	300 (25 years)
Mean	12.454
Std. error mean	0.361
Median	11.750
Mode	3.0
Sum	3736.310
Standard deviation	6.260
Variance	39.184
Minimum	-2.490
Maximum	47.560
Coefficient of variation	50.26

Source: Results from R-output

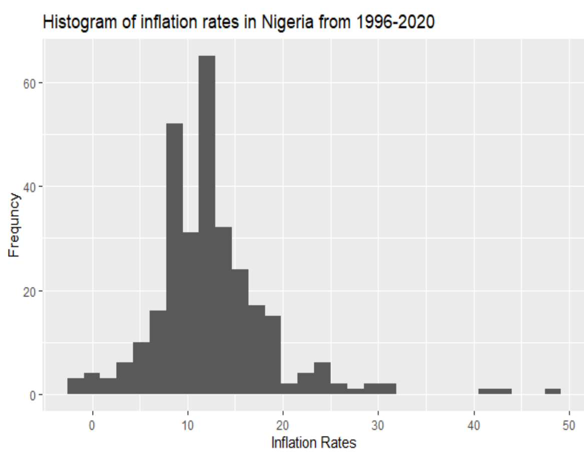

Figure 1: Histogram of Inflation Rates in Nigeria (1996-2020).

Figure 1 shows the histogram of the inflation rate data, indicating the presence of outliers in the dataset. The distribution of the series is skewed to the right (i.e. positively skewed).

Table 2: Augmented Dickey-Fuller (ADF) Test.

Dataset	Dickey-Fuller statistic	p-value	Remark
Original Inflation Data	-5.3636	0.001	Series is stationary

Source: R-output

ADF test shows that the original inflation rates series is stationary (P<0.05). There is no need for differencing. Hence seasonal difference, D = 0, and non-seasonal difference, d = 0.

Model Identification

In Figure 2, the monthly inflation rate in Nigeria from 1996 to 2020 is decomposed into four parts. The observed section indicates a decline in inflation values from 1996 to 2000, followed by fluctuating inflation rates with an average of 10 between 2010 and 2020. The trend component does not show a specific trend in inflation rates over the study period. The plot suggests that inflation has been rising as of 2020.

The decomposition analysis highlights a clear seasonal pattern in the inflation series, showing regular fluctuations throughout the year. Additionally, the random component suggests that the inflation rate series is approximately stationary, a finding supported by the results of the Augmented Dickey-Fuller (ADF) test (Table 2).

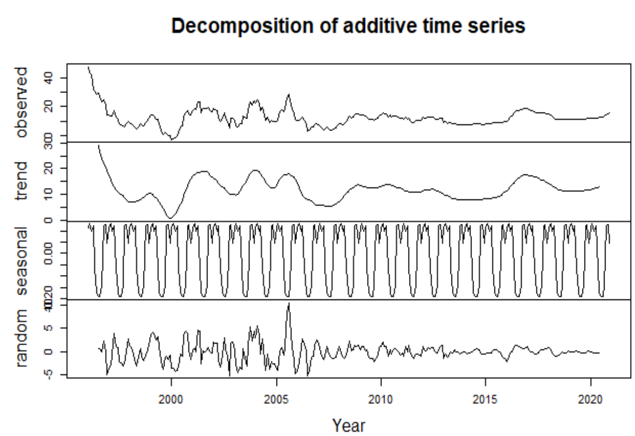

Figure 2: Decomposition of Inflation Rate Data (1996-2020).

The ACF plot of the inflation series, shown in Figure 3, reveals 3 significant spikes at seasonal lags (0.0, 1.0, and 2.0), indicating a potential seasonal moving average SMA(3) model. Additionally, 2 significant spikes at non-seasonal lags suggest a non-seasonal moving average MA(2). Based on this plot, the parameters Q=3 and q=2 can be established for the SARIMA(p,d,q)(P, D, Q)[12] model.

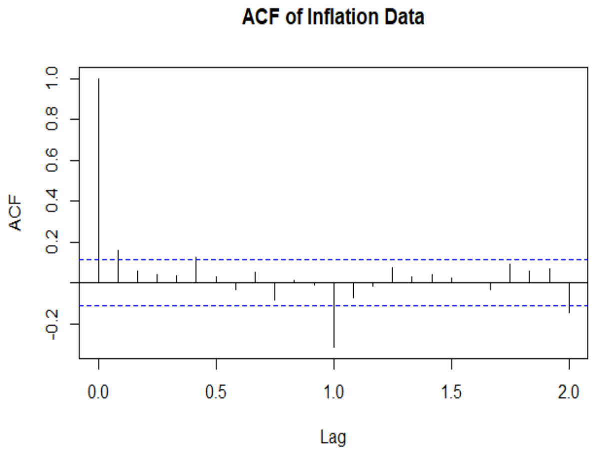

Figure 3: ACF Plot of Inflation Series.

In Figure 4, we observe the partial autocorrelation function (PACF) of the inflation rates series. There are three significant spikes in the seasonal lags (0.0, 1.0, and 2.0), suggesting a seasonal autoregressive SAR (3) model. Additionally, two significant spikes in the non-seasonal lags indicate a non-seasonal autoregressive AR (2) model. Based on this plot, we can set the values of p = 2 and P = 3 in SARIMA (p, d, q) (P, D, Q) [12]. The ACF and PACF plots lead to a SARIMA model with the following orders: d = 0, D = 0, p = 2, P = 3, Q = 3, and q = 2. Therefore, the initial model identified is SARIMA (2, 0, 2) (3, 0, 3) [12].

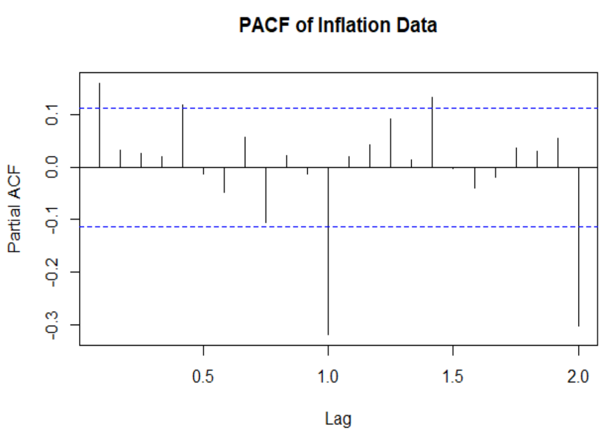

Figure 4: PACF Plot of Inflation Rates.

Table 4 presents SARIMA(2,0,2)(1,0,2)[12] which was the SARIMA model suggested by R-software (version 4.0.3) for the inflation rates series.

Table 4: Automatic SARIMA Model from R-Output.

```
> auto.arima(infdata, seasonal = 12)
        Series: infdata
        ARIMA(2,0,2)(1,0,2)[12] with non-zero mean
```

Source: R-output

Comparison of Multiple Models

The initial models, SARIMA(2,0,2)(3,0,3)[12] and SARIMA(2,0,2)(1,0,2)[12] earlier identified were compared with other possible models to identify the model with a minimum of AIC and BIC.

Table 5: Different Combinations of SARIMA Models by Several Metrics.

S/N	SARIMA Models SARMA(p,d,q)(P,D,Q)[12]	AIC	BIC
1	SARIMA(2,0,2)(3,0,3)[12]	1175.049*	1219.494*
2	SARIMA(2,0,2)(1,0,2)[12]	1170.207*	1203.541*
3	SARIMA(2,0,1)(2,0,1)[12]	1169.636**	1199.267**
4	SARIMA(1,0,2)(2,0,1)[12]	1173.270	1202.900
5	SARIMA(1,0,2)(1,0,1)[12]	1174.782	1200.709
6	SARIMA(1,0,1)(2,0,1)[12]	1173.859	1199.786

***The minimum of AIC, and BIC.*
**Initial model(s)*
Source: R-output

Table 5 presents six (6) different SARIMA models obtained from R-software and their AIC and BIC as accuracy measures. The model, SARIMA (2, 0, 1)(2, 0, 1)[12] is the best model with the minimum AIC and BIC.

Model Estimation

In Table 6, the estimate and significance test results for the parameters of the SARIMA(2,0,1)(2,0,1)[12] model are presented. The seasonal moving average parameter is statistically significant at a level of P<0.05. The model equation can be expressed as:

$$(1-B)^d(1-B^m)^D\varphi(B)\Phi(B)X_t = \theta(B)\Theta(B)\varepsilon_t$$
.
AR(1), AR(2), SAR(2), and SMA(1) terms are statistically significant at the 0.05 level. The MA(1) term is statistically significant at the 0.01 level. However, the SAR(1) term is not statistically significant.

$$(1-B^{12})X_t = \Theta(B)\varepsilon_t.$$

Substituting the model parameter gives rise to: $(1-B^{12})X_t = (1-1.0B^{12})\varepsilon_t$

$$(1-B)^d(1-B^m)^D\varphi(B)\Phi(B)X_t = \theta(B)\Theta(B)\varepsilon_t$$
.
Since d = 0 (non-seasonal difference) and D = 0 (seasonal difference), m = 12 (seasonal length),
The model equation becomes:

$$(1-B)^0(1-B^{12})^0\varphi(B)\Phi(B)X_t = \theta(B)\Theta(B)\varepsilon_t$$
.
$$1(1)\varphi(B)\Phi(B)X_t = \theta(B)\Theta(B)\varepsilon_t.$$

Hence the model equation is of the form $\varphi(B)\Phi(B)X_t = \theta(B)\Theta(B)\varepsilon_t$.

Setting the order of the model SARIMA (2,0,1)(2,0,1)[12], we set:

$$(1+\varphi_1 B)(1+\varphi_2 B)(1+\varphi_1 B^{12})X_t = (1+\theta_1 B)(1+\theta_2 B)(1 + \Theta_1 B^{12})\varepsilon_t$$

Substituting the model coefficients we have:

(1+1.6893B)(1-0.7006B)(1-0.4822B^{12}) X_t = (1+ 0.1038B) (1-0.1496B)(1-0.8137B^{12}) ε_t

Table 6: Model Coefficients for SARIMA(2,0,1)(2,0,1)[12].

Coefficients	Estimate	Std. Error	z value	Pr(>|z|)
AR(1)	1.6893	0.2004	8.4308	< 2.2e-16 ***
AR(2)	-0.7006	0.1995	-3.5075	0.0004524 ***
MA(1)	-0.4822	0.2462	-1.9591	0.0501022 .
SAR(1)	0.1038	0.0788	1.3177	0.1875900
SAR(2)	-0.1496	0.0726	-2.0607	0.0393328 *
SMA(1)	-0.8137	0.0671	-12.1261	< 2.2e-16 ***
Intercept	**12.903935**	**1.169273**	**11.0359**	**< 2.2e-16 *** **
AIC = 1169.636			**BIC = 1199.267**	

*Sig. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

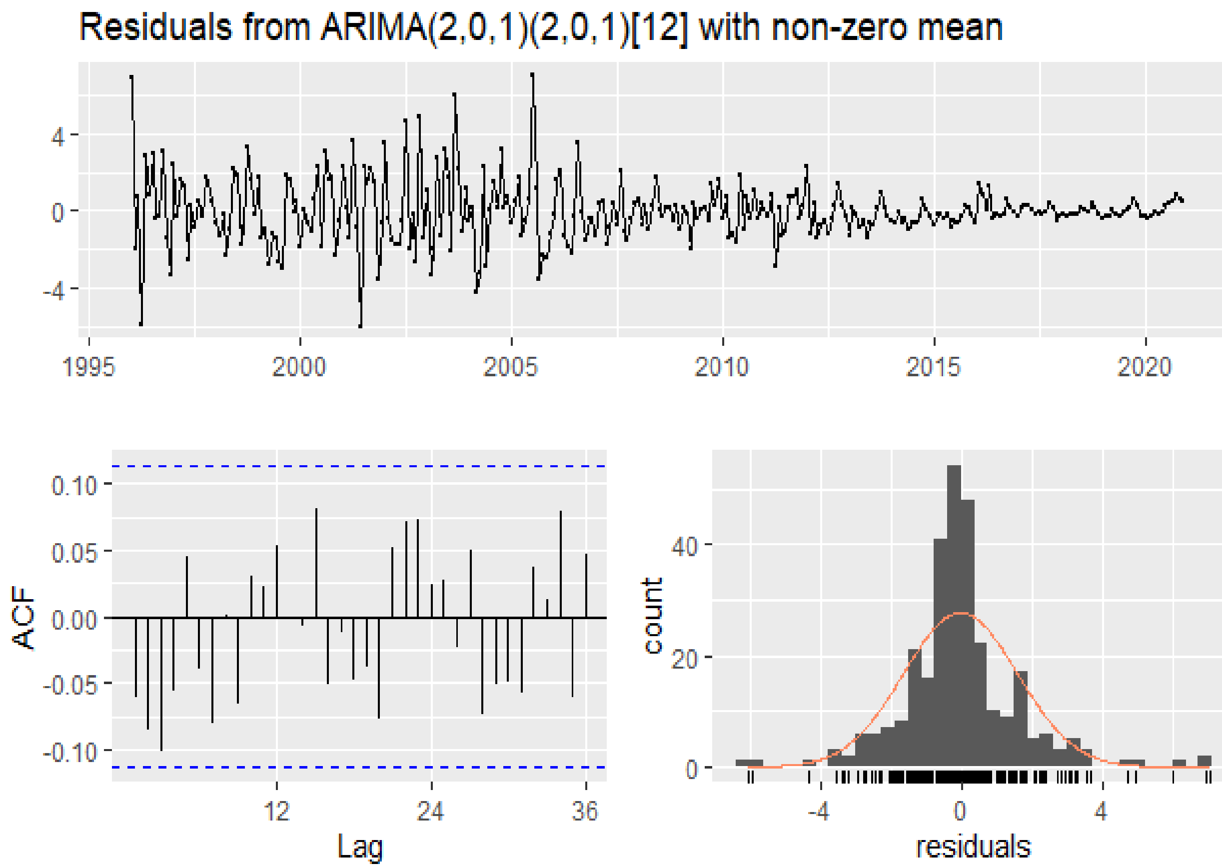

Figure 5: Residuals Plot.

Model Diagnostic Checks

In Figure 5, we have the time plot, ACF plot, and histogram of residuals from the SARIMA (2,0,1)(2,0,1)[12] model. The time plot indicates that the residuals are approximately stationary. The ACF plot shows that all the points are within the limit, suggesting that the model fits the data well. Additionally, the histogram indicates that the distribution of the residuals is approximately normal, with similar spread on both tails.

Figure 6 shows the plot of the original inflation rates series and the forecast obtained from SARIMA(2,0,1)(2,0,1)[12]. It is evident that the inflation in Nigeria is projected to increase from 2020 to 2022. Subsequently, the inflation rate is expected to decrease between 2023 and 2025, followed by a rise after 2025, stabilizing at approximately 12.499 from 2025 to 2030.

Table 7 presents the Ljung-Box test of residuals from SARIMA(2,0,1)(2,0,1)[12]. The P-value = 0.1245 (P>0.05) indicates the acceptance of the null hypothesis and hence, the residuals are independent.

Table 8 presents the forecast values of the inflation rate in Nigeria from June to December 2024-2025 and the 95% confidence intervals.

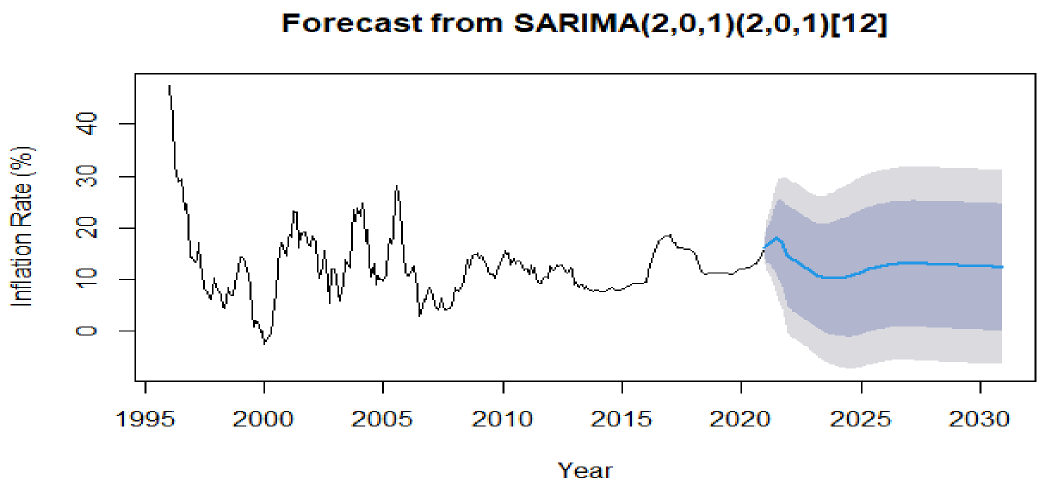

Figure 6: Forecast Plot of Inflation Rates in Nigeria (2021-2030).

Table 7: Ljung-Box Test of Residuals.

Series	Q*	p-value	Null Hypothesis
Residuals from SARIMA(2,0,1)(2,0,1)[12]	23.816	0.1245	Residuals are Independent

Source: R-output

Table 8: Forecast of Inflation Rate in Nigeria (2024-2025).

Month – Year	Point Forecast (X_t)	95% Confidence Intervals	
		Lower limit	Upper Limit
Jun-24	12.63637	-3.0880017	28.36073
Jul-24	12.6562	-3.0759185	28.38833
Aug-24	12.68309	-3.0559466	28.42213
Sep-24	12.71711	-3.0281479	28.46236
Oct-24	12.76083	-2.990055	28.51172
Nov-24	12.80479	-2.9512314	28.5608
Dec-24	12.84703	-2.9136785	28.60773
Jan-25	12.87053	-2.8919399	28.63299
Feb-25	12.89079	-2.8728555	28.65444
Mar-25	12.90754	-2.8569349	28.67201
Apr-25	12.91739	-2.8476755	28.68246
May-25	12.92733	-2.838188	28.69285
Jun-25	12.9355	-2.8303741	28.70137
Jul-25	12.93793	-2.8282256	28.70409
Aug-25	12.93674	-2.8296476	28.70313
Sep-25	12.93151	-2.8350787	28.6981
Oct-25	12.92004	-2.846715	28.6868
Nov-25	12.91003	-2.856885	28.67694
Dec-25	12.90378	-2.8632677	28.67082

Source: SARIMA (2,0,1)(2,0,1)[12]

DISCUSSION OF FINDINGS

Inflation in Nigeria has shown fluctuations over the period under study. The average inflation rate over the period from 1996 to 2020 was 12.454. An early decline in inflation was observed from 1996 to 2000, followed by an average rate of 10.0 between 2010 and 2020. By 2020, the inflation rate started to rise again. The trend plot of the inflation series indicates that there was no specific trend in inflation rates over the study period. The seasonal decomposition of the series reveals a regular seasonal pattern, with inflation showing a consistent rise and fall every year.

The Augmented Dickey-Fuller (ADF) test indicates that the Nigerian inflation rates series was stationary (D= -5.3636, $P<0.05$), consistent with the findings of Osuolale, *et al*. (2017). Initial analysis using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots suggested that SARIMA (2,0,2) (3,0,3) [12] could be a potential model for the inflation series. The Auto.Arima() function from the "forecast" package in R-software proposed SARIMA (2,0,2) (1,0,2) [12] as an appropriate model. A comparison of the possible models, along with a reduction in the number of parameters, revealed SARIMA (2,0,1) (2,0,1) [12] as the best fitting model for the Nigerian inflation rates series based on minimum AIC and BIC, contrary to the findings of Olatayo and Taiwo (2019). The forecast indicates an upturn in inflation in Nigeria between 2020 and 2022, with an average value of 14.92 expected between January 2021 and December 2022. This is reflected in the consistent increase in the prices of consumer goods in Nigeria since 2020 and up to the present moment in 2021. According to the fitted model, the inflation rate is projected to decrease between January 2023 and December 2025 to an average of 12.50. Subsequently, inflation in Nigeria is predicted to increase again to an average of 13.0 between July 2026 and July 2027, followed by a decrease to an average value of 12.692 between August 2027 and December 2030.

CONCLUSION

In summary, inflation in Nigeria has shown fluctuations over the study period. The average inflation rate from 1996 to 2020 is 12.454%. An analysis of the data indicates a initial decrease in inflation from 1996 to 2000, followed by a period of relative stability with an average of 10.0% from 2010 to 2020. However, inflation has been increasing since 2020. The trend plot of the inflation series does not show a specific trend in inflation rates over the study period.

The seasonal part of the analysis reveals a regular rise and fall in the inflation rates every year. Furthermore, the forecast suggests that inflation in Nigeria is expected to increase between 2020 and 2022, with an average value of 14.92% from January 2021 to December 2022. This explains the rising prices of consumer goods in Nigeria since 2020. According to the fitted model, the inflation rate is projected to decrease from January 2023 to December 2025, with an average of 12.50%. Subsequently, inflation in Nigeria is predicted to increase to an average of 13.0% from July 2026 to July 2027, followed by a reduction to an average value of 12.692% from August 2027 to December 2030. Hence, this work suggests that the government ought to adopt additional policies, such as stringent fiscal measures (increased taxation), supply-side regulations, wage management, appreciation of the exchange rate, and regulation of the money supply to curb inflation. Furthermore, the Nigerian government and its regulatory bodies should enforce strategies to manage the projected inflation trends in the country and take steps to safeguard the economy from entering a recession.

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Appendix A: Nigerian Inflation Rate Data from 1996-2020.

Year	Months											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1996	47.56	43.65	41.9	31.84	31.04	28.84	29.51	26.71	23.66	24.63	20.86	14.31
1997	14.32	13.35	13.75	17.09	12.85	11.65	8.31	7.71	6.53	6.34	8.11	10.21
1998	8.82	8.19	6.96	5.04	4.43	6.34	8.58	7.33	6.98	9.02	10.86	11.91
1999	14.29	14.38	13.55	11.58	11.36	8.28	3.98	0.76	2.24	1.48	-0.04	0.22
2000	-2.49	-1.73	-1.43	-0.05	2.17	5.87	6.67	13.1	15.51	17.08	15.38	14.53
2001	17.64	18.59	18.2	23.23	22.96	16.06	19	18.71	19.12	19.33	17.43	16.49
2002	18.55	17.99	17.38	12.76	10.18	12.22	15.57	12.28	9.97	5.37	12.15	12.17
2003	10.59	7.27	5.86	8.27	8.67	13.99	12.92	12.44	18.37	23.6	21.29	23.81
2004	22.39	24.85	22.46	17.54	19.78	14.1	10.68	13.01	9.13	10.73	10.05	10.01
2005	9.84	10.94	16.27	17.93	16.82	18.57	26.12	28.21	24.32	18.6	15.12	11.57
2006	10.71	10.84	12.04	12.56	10.55	8.49	3	3.75	6.25	6.13	7.76	8.55
2007	7.97	7.08	5.25	4.22	4.64	6.43	4.83	4.21	4.12	4.55	5.16	6.56
2008	8.57	8.03	7.78	8.17	9.7	12.05	13.95	12.36	13.02	14.74	14.83	15.06
2009	14.03	14.58	14.37	13.27	13.21	11.19	11.09	11.05	10.39	11.59	12.37	13.93
2010	14.4	15.65	14.81	15.04	12.91	14.1	13	13.7	13.6	13.4	12.8	11.8
2011	12.1	11.1	12.8	11.3	12.4	10.2	9.4	9.3	10.3	10.5	10.5	10.3
2012	12.6	11.9	12.1	12.9	12.7	12.9	12.8	11.7	11.3	11.7	12.3	12
2013	9.03	9.54	8.59	9.05	8.96	8.35	8.68	8.23	7.95	7.81	7.93	7.96
2014	7.98	7.71	7.78	7.85	7.96	8.17	8.28	8.53	8.32	8.06	7.93	7.98
2015	8.16	8.36	8.49	8.66	9	9.17	9.22	9.34	9.39	9.3	9.37	9.55
2016	9.62	11.38	12.77	13.72	15.58	16.48	17.13	17.61	17.85	18.33	18.48	18.55
2017	18.72	17.78	17.26	17.24	16.25	16.1	16.05	16.01	15.98	15.91	15.9	15.37
2018	15.13	14.33	13.34	12.48	11.61	11.23	11.14	11.23	11.28	11.26	11.28	11.44
2019	11.37	11.31	11.25	11.37	11.4	11.22	11.08	11.02	11.24	11.61	11.85	11.98
2020	12.13	12.2	12.26	12.34	12.4	12.56	12.82	13.22	13.71	14.23	14.89	15.75

Source: Nairametrics (https://nairalytics.com/download-inflation-rates)
R package output

Appendix B: Ten (10) Years Forecast of Inflation Rates In Nigeria (2021-2030).

Month-Year	Point Forecast	95% Confidence Interval	
		Lower Limit	Upper Limit
Aug-24	10.71222	-7.27813978	28.70258
Sep-24	10.83816	-7.25572651	28.93205
Oct-24	10.98949	-7.19846054	29.17744
Nov-24	11.14644	-7.12612036	29.41901
Dec-24	11.31148	-7.03640242	29.65937
Jan-25	11.43749	-6.95505842	29.83004
Feb-25	11.57368	-6.85283633	30.0002
Mar-25	11.71302	-6.74009496	30.16613
Apr-25	11.83509	-6.63849225	30.30867
May-25	11.96612	-6.52266783	30.4549
Jun-25	12.0888	-6.41077424	30.58837
Jul-25	12.1945	-6.31227305	30.70127
Aug-25	12.28754	-6.22363047	30.79871
Sep-25	12.3677	-6.145807	30.8812
Oct-25	12.43296	-6.08150121	30.94742
Nov-25	12.5	-6.01466467	31.01466
Dec-25	12.57296	-5.94170156	31.08763
Jan-26	12.65051	-5.86434665	31.16537
Feb-26	12.72525	-5.79038586	31.24088
Mar-26	12.79777	-5.71955432	31.3151
Apr-26	12.85919	-5.66102813	31.3794
May-26	12.91631	-5.60818408	31.4408
Jun-26	12.97435	-5.5559447	31.50464
Jul-26	13.01898	-5.51872076	31.55668
Aug-26	13.04881	-5.49791658	31.59555
Sep-26	13.06163	-5.49572791	31.61898
Oct-26	13.05822	-5.51127452	31.62771
Nov-26	13.05066	-5.53238049	31.6337
Dec-26	13.03834	-5.55950453	31.63619
Jan-27	13.04301	-5.56565747	31.65167
Feb-27	13.04003	-5.5792148	31.65927
Mar-27	13.0327	-5.5973199	31.66273
Apr-27	13.02891	-5.61207566	31.66989
May-27	13.01744	-5.63455794	31.66945
Jun-27	13.0073	-5.65566115	31.67027
Jul-27	12.99991	-5.67384706	31.67367
Aug-27	12.99295	-5.69133607	31.67724
Sep-27	12.9861	-5.70835862	31.68056
Oct-27	12.98044	-5.72375369	31.68463
Nov-27	12.9703	-5.74311932	31.68373
Dec-27	12.95365	-5.7684389	31.67574
Jan-28	12.93505	-5.79465443	31.66475
Feb-28	12.91361	-5.82300396	31.65022
Mar-28	12.88969	-5.85316904	31.63254
Apr-28	12.86896	-5.87949105	31.61741
May-28	12.84629	-5.90711424	31.5997
Jun-28	12.82093	-5.93680522	31.57867
Jul-28	12.79998	-5.96149848	31.56145
Aug-28	12.78377	-5.98088681	31.54842
Sep-28	12.7734	-5.99390764	31.54071
Oct-28	12.76882	-6.00067036	31.5383
Nov-28	12.76345	-6.00778375	31.53468
Dec-28	12.75734	-6.01525145	31.52994
Jan-29	12.74124	-6.03312046	31.5156
Feb-29	12.72668	-6.0492322	31.50258

Mar-29	12.71231	-6.06485776	31.48947
Apr-29	12.69559	-6.08256377	31.47374
May-29	12.68099	-6.09790811	31.45989
Jun-29	12.66429	-6.11514968	31.44373
Jul-29	12.64623	-6.1335887	31.42605
Aug-29	12.62808	-6.15197463	31.40814
Sep-29	12.61034	-6.16986131	31.39054
Oct-29	12.59259	-6.18767214	31.37286
Nov-29	12.57646	-6.20382577	31.35675
Dec-29	12.56303	-6.21726173	31.34332
Jan-30	12.5486	-6.23169096	31.32889
Feb-30	12.53577	-6.24451723	31.31607
Mar-30	12.52425	-6.25606147	31.30455
Apr-30	12.51099	-6.26935889	31.29134
May-30	12.49932	-6.28111042	31.27975
Jun-30	12.48891	-6.29164269	31.26946
Jul-30	12.47665	-6.3040815	31.25738
Aug-30	12.46267	-6.31828508	31.24363
Sep-30	12.44662	-6.33461816	31.22787
Oct-30	12.42853	-6.35305761	31.21011
Nov-30	12.4118	-6.3701729	31.19378
Dec-30	12.39668	-6.38573762	31.17911

Source: SARIMA(2,0,1)(2,0,1)[12]

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