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# Modeling and Forecasting Inflation Dynamics in Nigeria: A Time Series Approach

**Nasiru Yakubu[a]*, Habeeb R. Abdulrahman[a], Adamu Abubakar[b] and Ikrimat A. Babando[c]**

[a]*Department of Statistics, Faculty of Physical Sciences, Modibbo Adama University, Yola, Adamawa State, Nigeria*

[b]*Department of Mathematical Sciences, Faculty of Science, Gombe State University. Gombe State Nigeria*

[c]*Department of Early Child Care and Education, College of Education Zing, Taraba State Nigeria*

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**A B S T R A C T**

This study utilized an Auto Regressive Integrated Moving Average (ARIMA) Model to forecast Nigeria's inflation rate, leveraging monthly data from January 2015 to May 2024 to predict trends from June 2024 to September 2027. The ARIMA model, identified as (3,2,2)(0,0,2)(12) based on the Akaike Information Criteria (AIC), forecasts a persistent upward trend in inflation, with increasing uncertainty over time. The findings suggest that Nigeria's inflation rate will continue to raise steadily over time next three years, posing significant economic challenges, including decreased purchasing power and unstable economic growth. The study's results underscore the importance of prudent economic policy making to mitigate the effects of inflation. To manage the inflationary pressures, the study suggests implementing monetary tightening measures, maintaining exchange rate stability, and conducting regular economic monitoring to inform timely policy interventions. The research demonstrates the utility of ARIMA models in informing policy decisions and highlights the need for continued vigilance in economic management. By providing valuable insights into future inflation trends, the study contributes to the development of effective economic policies that promote stability and growth in Nigeria. The study's findings have implications for policymakers, economists and stakeholders seeking to understand and address the challenges posed by inflation in Nigeria.

## 1. Introduction

In economics, a regular rise in the price of goods and services available to the populace in an economy within a given time frame is referred to as inflation. The consumer price index (CPI) can be said to be used more often in the measurement of inflation. Monetary authorities' main objective is to regulate inflation and keep inflation rate under control because this factor is deemed to be a crucial challenge in transition economies. Thus, value of purchased national currency may decrease due to inflation, which, in turn implies the deterioration of the socioeconomic situation and people's quality of life causing uncertainty elsewhere, high costs also pose a major threat of dissuading both domestic and foreign investors from investing in the economy. Higher prices for domestic commodities also prevail on the regional and international markets erode the nation's terms of trade. Scholars also suggest that sharp increases in macroeconomic variables such as exchange rate and petroleum pump price result to significant increase in Inflation rate (Danrimi *et al*., 2024).

Nigeria has gone through a lot of changes in its political journey whereby the inflation has not remained constant but has changed for various reasons in the last 60 years. This has led to several researchers and scholars

* Corresponding author. Tel.: +234 8037248575
E-mail address: yakubunasir16442@gmail.com (Yakubu Nasiru)
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showing interest on the historical changes of inflation rates with regard to the economy and level of living.
Time series forecasting analysis has been applied extensively for decades in economics by providing researchers and economists with valuable insights on future economic trend. One of the most popular and important application of the timeseries analysis in economic is the modeling and forecasting of future behavior pattern of macroeconomic variables. Thus, various authors made numerous efforts to contribute into the sphere of inflation rate forecasting. For example, Stock and Watson (2008) provided a survey to compare different methods and showed that the Phillips curve-based models were appropriate for short-term forecast of the U. S. inflation rate.

Nyoni and Nathaniel (2021), compares ARIMA and GARCH models for forecasting inflation in Kenya, providing insights into the performance of ARIMA in a developing economy context. Iqbal and Naveed (2021) also employ the ARIMA and functional time series models in forecasting inflation rate in Pakistan, offering a comparative analysis of different forecasting techniques. Hasanov and Ucar (2020), in their study, examines various model selection approaches for inflation forecasting, including ARIMA models, providing insights into model selection criteria.
Pincheira and Medel (2021) While not exclusively focused on ARIMA, their study compares various forecasting methods, including ARIMA, for inflation prediction in Chile. Jere and Siyanga (2022) In their study apply ARIMA models to forecast inflation in Zambia, providing a case study from an African economy.
In a different African study, Nyoni (2018) used annual time series data from 1960 to 2017 to model inflation in Kenya using the ARIMA and GARCH models. The results showed that the ARIMA (2, 2, 1) model, the ARIMA (1, 2, 0) model, and the AR (1) – GARCH (1, 1) model are all useful models for predicting inflation in Kenya. Nyoni & Nathaniel (2019) used time series data on inflation rates from 1960 to 2016 using ARMA, ARIMA, and GARCH models to study inflation in Nigeria. Based on the existing literatures, the majority attempted to identify the impact of inflation rate on the Nigerian GDP using ARIMA, SARIMA and GARCH time series models. The transitional system of government in Nigeria has necessitated this study by using ARIMA Box-Jenkins approach to model and forecast inflation rate in Nigeria from June, 2024 to September, 2027.

Therefore, this study will update and evaluate the effectiveness of the ARIMA model in forecasting inflation in Nigeria, assess the accuracy of the ARIMA model by comparing the error metrics with other traditional forecasting models, identify the trends contributing to inflation dynamics in Nigeria, using the ARIMA model and provide policy recommendations based on the model's forecasting performance and its potential for improving inflation management in Nigeria.

## 2. Materials and Methods

### 2.1 Data source for the study

The study used data on inflation rate extracted from the Central Bank of Nigeria (CBN) website https:/www.cbn.ng. The data were extracted from January 2015 to May 2024. The R statistical programming software was used for the analysis of the data. This is a powerful statistical software package that allows users to analyze, manage and produce graphical displays of data.

### 2.2 Model Specification

A model is a simplified system used to simulate certain aspects of the real economy. The method specified for this study is the Box-Jenkins approach (Box and Jenkins, 1976), which incorporates the Autoregressive Integrated Moving Average (ARIMA) model. The ARIMA model seeks to identify patterns in historical data and decomposes it into three main components and they include; an autoregressive (AR) process, which reflects the memory of past events; an integrated (I) process, which accounts for stabilizing or making the data stationary, thus making it valid for forecasting; and a moving average (MA) process, which models the forecast error (Deebom, Essi & Amos,2021). The longer the historical data, the more accurate the forecast, as the model learns over time (Otu *et al.,* 2014). These components combine and interact with each other, eventually forming the ARIMA(p,d,q) model. The first component, the AR term, uses the p lags of a time series to improve the forecast. The AR part of ARIMA indicates that the evolving variable of interest is regressed on its own lagged (previous) values. An AR(p) model is expressed in the following form, as shown in equation 1:

$$Y_t = \varphi_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \epsilon_t \quad (1)$$

Where;

$Y_t$= The response (dependent) variable being forecasted at time t
$Y_{t-1}$= The lag of the series or the response variable at time lag (Stimulus)
$\varphi_1 \ldots \varphi_p$= Are the coefficient of lag that the model estimates
$\varphi_0$= Is the intercept term also estimated by the model
$\epsilon_t$ = Error term at time t

This equation demonstrates that the forecasted value of inflation at time t depends on its value in the previous period and a constant. The second component is the integrated stochastic process. A time series is said to be integrated of the first order, I(1), if it must be differenced once to make it stationary. In general, if a time series must be differenced d times to become stationary, it is said to be integrated of order d, denoted as I(d) (Gujarati, 2003).

Similarly, the third component, the MA(q) model, uses the q lags of forecast errors to improve the forecast. The MA part indicates that the regression error is a linear combination of error terms whose values occurred both contemporaneously and at various points in the past. An MA(q) model has the form shown in equation 2.

$$Y_t = \theta_0 + \theta_1 \epsilon_{(t-1)} + \theta_2\epsilon_{t-2} + \cdots + \theta_q \epsilon_{(t-q)} + \epsilon_t \quad (2)$$

Where:
$Y_t$= The response (dependent) variable being forecasted at time t
$\theta_0$= The constant mean of the process
$\theta_1, \theta_2 \ldots \theta_q$= The coefficient to be estimated
$\epsilon_t$= is the error term at time t
$\epsilon_{(t-1)}, \epsilon_{t-2} \ldots \epsilon_{(t-q)}$= the error in previous time that are incorporated in the response $Y_t$.

This equation indicates that **y** at time **t** is equal to a constant plus a moving average of the current and past white noise error terms. However, if no differencing is required to make the series stationary, then an ARMA model is generated with **d** equal to zero. The autoregressive moving average (ARMA) model refers to a model with **p** autoregressive terms and **q** moving average terms. An ARMA(p, q) model is stationary if the series is stationary, as shown in equation 3.

$$y_t = \varepsilon_t + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \quad (3)$$

ARMA model is a combination of the simple AR and MA model of order (p,q) called autoregressive moving average (ARMA). To create an ARIMA model, we begin by combining or adding both the autoregressive (AR) process, the moving average (MA) process and the integrated part (I) together as shown in equation (4)

$$Y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots \varphi_p y_{t-p} + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \cdots + \theta_q\epsilon_{t-q} + \epsilon_t. \quad (4)$$

Where $\epsilon t$ is a purely random process with mean zero and variance $\sigma^2$

**2.3 ARIMA model Estimation Procedures**

Model Identification: Identify the appropriate ARIMA model for your data by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. These plots helps to determine the orders of the autoregressive (AR) and moving average (MA) components, as well as the differencing parameter (d) required to achieve stationarity.

Parameter Estimation: Estimate the parameters of the ARIMA model using techniques such as maximum likelihood estimation (MLE) or least squares estimation. This step involves fitting the model to the data and determining the optimal values for the model parameters.

Model Diagnostics: Evaluate the goodness of fit of the ARIMA model to the data by examining diagnostic statistics, such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). Additionally, assess the residuals of the model to ensure that they are white noise and do not exhibit any systematic patterns

Model Forecasting: Once you have a satisfactory ARIMA model has been obtained, it shall be used to generate forecasts for future time periods.

## 3. Results and Discussion

The data utilized in this analysis comprises monthly inflation rates in Nigeria from January 2015 to May 2024. The dataset provides insights into the inflationary trends over this period, capturing both short-term fluctuations and long-term trends. A summary of the data is as follows:

Table 1: Summary Statistics of Nigeria Inflation Rates (2015-2024)

| **Statistics** | **Value** |
|---|---|
| Minimum Value: | 8.20% |
| 1st Quartile (Q1): | 11.40% |
| Median: | 15.70% |
| Mean: | 16.11% |
| 3rd Quartile (Q3): | 18.17% |
| Maximum Value: | 33.95% |

This summary indicates a wide range in inflation rates, with a noticeable increase in recent years, as shown in the time plot displayed in figure 1, which is also particularly reflected in the maximum value.

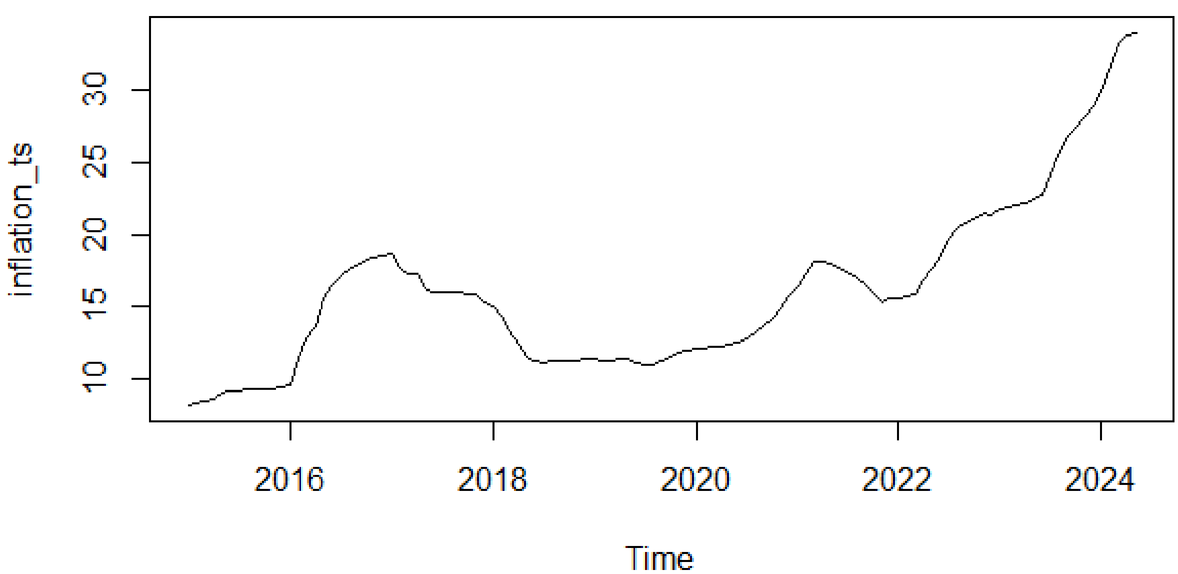


Figure 1: Time series plot of monthly Nigerian inflation rates (January 2015 - May 2024)

**Time Series Decomposition**

To better understand the underlying components of the inflation data, a time series decomposition was performed. This decomposition breaks down the series into three components: trend, seasonal, and irregular.

**Trend**: The trend component as shown in figure 2 revealed a general upward path in inflation over the observed period, indicating persistent inflationary pressures in the Nigerian economy.

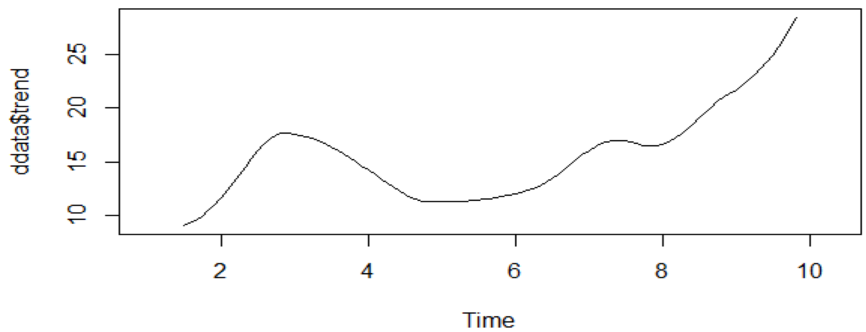


**Figure 2: Trend of Nigerian Inflation**

**Seasonality**: A recurring seasonal pattern was detected as shown in figure 3 with certain months consistently showing higher or lower inflation rates. This could be tied to specific economic activities or policy changes that occur regularly within the year.

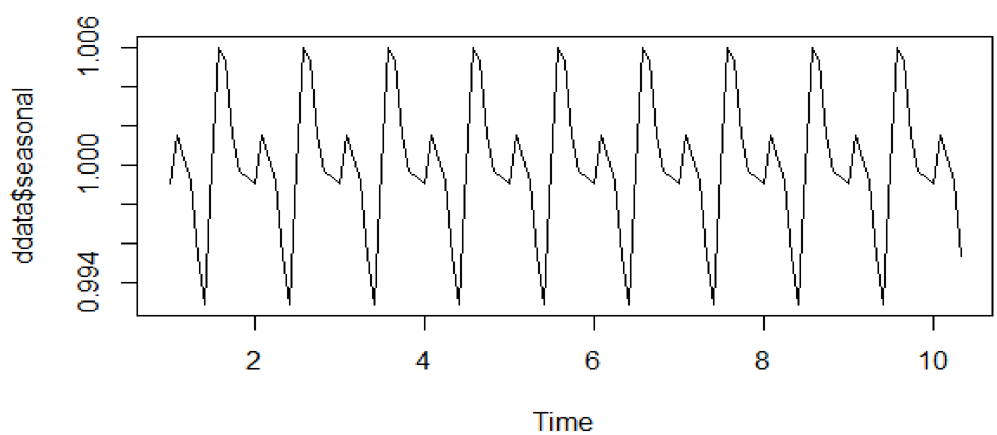


Figure 3: Seasonality pattern of Nigerian Inflation

**Irregular Component**: The irregular component captured the random fluctuations in the data that could not be explained by the trend or seasonal patterns. This is displayed in figure 4

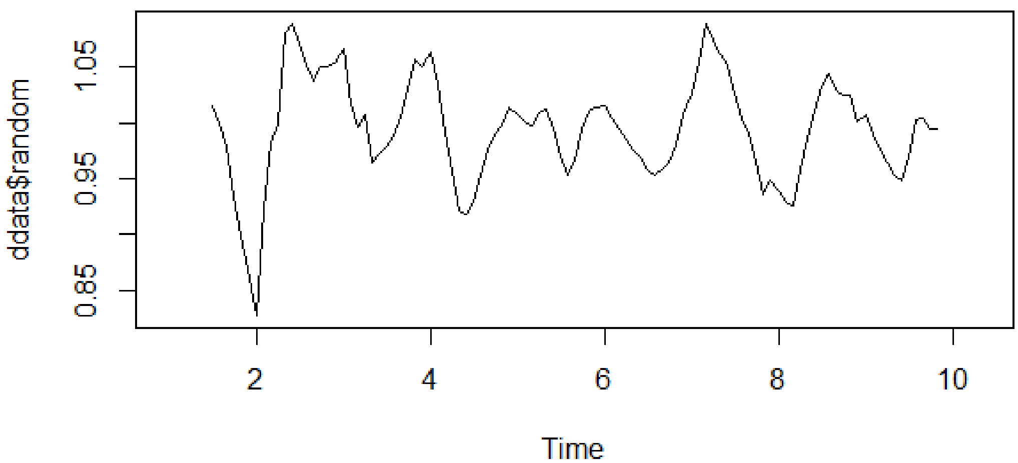


Figure 4: Random component of Nigerian Inflation

## Stationarity Test

For ARIMA modeling, it is crucial that the time series data are stationary. The Augmented Dickey-Fuller (ADF) test was used to assess the stationarity of the inflation series.

**Initial ADF Test:** The initial test returned a p-value of 0.9535, indicating that the series was non-stationary, meaning it had a unit root and its statistical properties, such as mean and variance, were not constant over time.

**Differencing:** To achieve stationarity, the series was differenced twice. Differencing is a technique used to remove trends and seasonality, making the series more stable over time.

**Post-Differencing ADF Test:** After differencing, the ADF test returned a p-value of 0.01, confirming that the series was now stationary, and suitable for ARIMA modeling. The time plot after second differencing is shown in figure 5

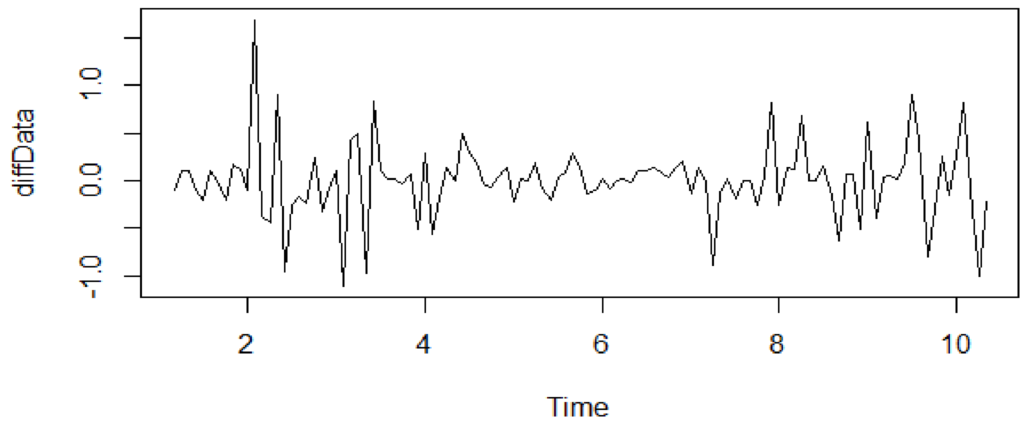


Figure 5: Plot of Nigerian Inflation after differencing

## Model Identification

The identification of the appropriate ARIMA model was done using the `auto.arima` function in R. This function automatically selects the best ARIMA model by evaluating different combinations of autoregressive (AR), differencing I(d), and moving average (MA) parameters based on the Akaike Information Criterion (AIC).

Table 2: Possible ARIMA models

| Model | AIC |
|---|---|
| ARIMA(2,2,2)(1,0,1)[12] | : 90.04842 |
| ARIMA(1,2,0)(1,0,0)[12] | : 106.5645 |
| ARIMA(0,2,1)(0,0,1)[12] | : 98.25867 |
| ARIMA(2,2,2)(0,0,1)[12] | : 88.02492 |
| ARIMA(2,2,2) | : 98.85119 |
| ARIMA(2,2,2)(0,0,2)[12] | : 85.56764 |
| ARIMA(2,2,2)(1,0,2)[12] | : 87.68266 |
| ARIMA(1,2,2)(0,0,2)[12] | : 87.07369 |
| ARIMA(2,2,1)(0,0,2)[12] | : 86.78899 |
| ARIMA(3,2,2)(0,0,2)[12] | : 85.1422* |
| ARIMA(3,2,2)(1,0,2)[12] | : 89.68221 |
| ARIMA(3,2,1)(0,0,2)[12] | : 88.7885 |
| ARIMA(4,2,2)(0,0,2)[12] | : 85.93698 |
| ARIMA(3,2,3)(0,0,2)[12] | : 86.7151 |
| ARIMA(2,2,3)(0,0,2)[12] | : 86.10653 |
| ARIMA(4,2,1)(0,0,2)[12] | : 86.77858 |
| ARIMA(4,2,3)(0,0,2)[12] | : 86.04393 |

* Model selected

**Selected Model:** The model ARIMA(3,2,2)(0,0,2)[12] is identified as the best model for forecasting Nigeria's inflation this is because it has the minimum value of AIC=85.1422. This model suggests three autoregressive terms, two integration, two moving average terms and two seasonal moving average.

## Model Fitting

The ARIMA(3,2,2)(0,0,2)[12] model was then fitted to the data. The coefficients obtained from the model fitting are as follows:

AR (1): -0.0446

AR (2): 0.4603

AR (3): 0.1721

MA (1): -0.0760

MA (2): -0.8424

SMA (1): -0.3599

SMA (2): -0.2896

The model's sigma squared value is 0.1087, and the AIC value is 85.14, indicating a good fit to the data.

## Residual Analysis

After fitting the model, it is important to analyze the residuals to ensure that they behave like white noise, meaning they have a mean of zero, constant variance, and no autocorrelation.

Residual Plots: The residuals were plotted, and their ACF and PACF in figures 6 and 7, respectively were analyzed. The plots showed that the residuals did not exhibit any significant patterns or autocorrelations, indicating that the model successfully captured the underlying structure of the data.

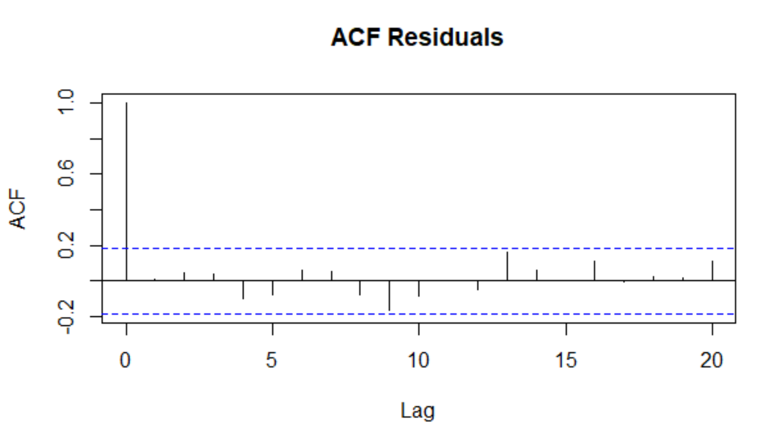


Figure 6: ACF Plot of Residual

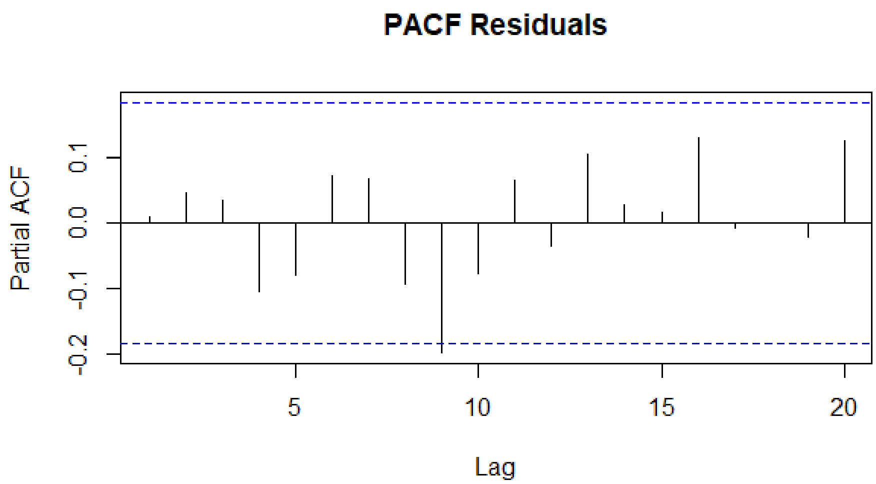


Figure 7: PACF Plot of Residual

**Forecasting**

Using the fitted ARIMA model, forecasts of Nigeria's inflation rate were generated for the next three years, from June 2024 to September 2027. The forecasted values, along with the 95% confidence intervals, are presented in table 4.1:

**Table 3: Forecast of Inflation Rates**

| Month | Point Forecast | Confidence Interval | |
|---|---|---|---|
| | | Low | High |
| Jun-24 | 34.18 | 33.54 | 34.83 |
| Jul-24 | 34.03 | 32.65 | 35.41 |
| Aug-24 | 33.72 | 31.66 | 35.79 |
| Sep-24 | 33.94 | 31.10 | 36.79 |
| Oct-24 | 34.28 | 30.67 | 37.90 |
| Nov-24 | 34.49 | 30.08 | 38.90 |
| Dec-24 | 34.76 | 29.56 | 39.97 |
| Jan-25 | 34.78 | 28.77 | 40.78 |
| Feb-25 | 34.66 | 27.86 | 41.45 |
| Mar-25 | 34.61 | 27.02 | 42.20 |
| Apr-25 | 34.88 | 26.50 | 43.26 |
| May-25 | 35.29 | 26.12 | 44.46 |
| Jun-25 | 35.59 | 25.72 | 45.46 |
| Jul-25 | 35.62 | 25.11 | 46.12 |
| Aug-25 | 35.52 | 24.40 | 46.64 |
| Sep-25 | 35.69 | 24.00 | 47.39 |
| Oct-25 | 35.98 | 23.72 | 48.23 |
| Nov-25 | 36.17 | 23.36 | 48.97 |
| Dec-25 | 36.36 | 23.01 | 49.70 |
| Jan-26 | 36.45 | 22.57 | 50.32 |
| Feb-26 | 36.34 | 21.93 | 50.74 |
| Mar-26 | 36.30 | 21.37 | 51.23 |

| | | | |
|---|---|---|---|
| Apr-26 | 36.51 | 21.05 | 51.97 |
| May-26 | 36.82 | 20.83 | 52.81 |
| Jun-26 | 37.09 | 20.62 | 53.56 |
| Jul-26 | 37.37 | 20.44 | 54.29 |
| Aug-26 | 37.64 | 20.29 | 55.00 |
| Sep-26 | 37.91 | 20.14 | 55.68 |
| Oct-26 | 38.18 | 20.01 | 56.36 |
| Nov-26 | 38.45 | 19.89 | 57.02 |
| Dec-26 | 38.72 | 19.77 | 57.68 |
| Jan-27 | 38.99 | 19.65 | 58.33 |
| Feb-27 | 39.26 | 19.54 | 58.98 |
| Mar-27 | 39.53 | 19.43 | 59.63 |
| Apr-27 | 39.80 | 19.32 | 60.27 |
| May-27 | 40.06 | 19.21 | 60.91 |
| Jun-27 | 40.33 | 19.10 | 61.56 |
| Jul-27 | 40.60 | 18.99 | 62.20 |
| Aug-27 | 40.86 | 18.88 | 62.85 |
| Sep-27 | 41.13 | 18.77 | 63.49 |

The forecast indicates a continuing upward trend in inflation, with increasing uncertainty as the forecast horizon extends. The widening confidence intervals reflect this uncertainty, emphasizing the potential for significant variability in future inflation rates.

## 4. Conclusion

The study successfully applied an ARIMA model to forecast Nigeria's inflation rate, providing valuable insights into the future trajectory of inflation in the country. The forecasted rising trend in inflation underscores the importance of effective economic policies to manage inflationary pressures and ensure sustainable economic growth. As inflation remains a critical issue for Nigeria, accurate forecasting and timely policy interventions will be essential in safeguarding the economy's stability and prosperity. The forecasted increase in inflation suggests the need for vigilant and proactive economic policies. The Central Bank of Nigeria (CBN) may need to consider tightening monetary policy, such as increasing interest rates, to curb inflationary pressures. Additionally, fiscal policies that stabilize the exchange rate and manage public spending effectively could help mitigate inflation.

Regular monitoring of inflation rates and economic indicators is crucial. The government should be prepared to intervene when necessary to stabilize the economy, particularly if inflation begins to exceed projected levels. Future research should consider incorporating exogenous variables, such as global oil prices, exchange rates, and GDP growth, to improve the accuracy and robustness of the forecasts. Additionally, exploring alternative models like VAR (Vector Autoregression) or GARCH (Generalized Autoregressive Conditional Heteroskedasticity) might provide further insights.

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