AN EXPLORATION OF NIGERIAN EXCHANGE RATE USING ARIMA MODEL

Abstract

Exchange rate fluctuations have long been a central topic in Nigerian economic discussions, particularly due to the country's heavy reliance on imports and oil exports. As a developing nation, Nigeria is especially susceptible to external shocks. Thus, this study forecasts the exchange rate fluctuations between the US Dollar and the Nigerian Naira, utilizing monthly data from January 2009 to May 2024 and sourced from the Central Bank of Nigeria (CBN) website. The data were analyzed using the ARIMA process and KPSS methods for testing the stationarity of the series, with 185 data points. The ARIMA (4, 2, 2) model was selected based on the AIC and BIC values as the best-fitted model. The results indicated a rise in the exchange rate, from the value of 1509.352 Naira in June 2024 to between 2370.834 Naira by January, 2025 and 3755.827 Naira in January of 2026. Considering the decline in the forecast of Naira's value against the Dollar, it is recommended that policymakers consider these components when designing monetary policies aimed at stabilizing the foreign exchange market and the overall economy.

Keywords: Exchange Rate, Autoregressive, Moving Average, Crypto currency, Unit Roots.

1.0 Introduction

The issue of exchange rate fluctuation is not new in Nigeria's economic debate as the country relies heavily on import and exports of oil which makes movement of exchange rates costly. As the economy remains underdeveloped, external shocks have pronounced impacts on Nigeria. These shocks can have direct impacts on its exchange rate. These shocks could be, for example price changes of all commodities worldwide or some kind of international monetary policy action. Recent volatility in both the Naira official rate as well as the black-market stems mainly from declining foreign exchange reserves and shifts in global oil prices coupled with policy makers revising their decisions on how best to manage exchange rate levels.

According to Varenius (2017), Foreign Exchange Market is the most important of all the trade locations. Globalization is primarily responsible for changes in exchange rates and macroeconomic indicators that affect a country, including performance levels, international trade, and industrial capacity utilization. Because of this, it's critical for economists to understand what influences exchange rates so they can anticipate and plan ahead for any necessary policy responses. However, the instability of oil prices and the resulting economic vulnerabilities from slowing production processes and weakening local currencies are the major problems. The effect of significant events, such as the 2008 global financial crisis (GFC), the 2016 economic meltdown, and more recently, COVID-19, on currency rates and the domestic economy serve as underlined factors. Fiscal and monetary measures were necessary to combat distortion. After being rebased, the GDP increased by 8.4% yearly on average between 2000 and 2010. The economy shrink by 2.7% in 2015, and subsequent to the 2016 oil price shock, there have been additional economic downturns.

Furthermore, Nigeria's volatile exchange rate has not only weakened productivity but also hindered economic growth, with average growth from 2014 to 2023 being 1.98 percent, down from an average of 6.73 percent for the twelve years prior. It should come as no surprise, then, that during the previous ten years, productivity has grown at a pitiful average yearly rate of 1.95 percent. Exchange rate fluctuations do not only restrict companies' ability to import raw and intermediate materials, but also increase their operational costs, which lowers their productive capacity, lowers product quality, and ultimately reduces their competitiveness (Olofin and Orisadare, 2023).

Despite decreasing in 2020, annual growth continued to be slow, averaging 3.0 percent. Prior to increasing to US$/N118.99 by 2008, the exchange rate was averaging about US$/N130.00 per year. Nevertheless, the Naira declined after the global financial crisis (GFC) and kept going downhill, hitting US$/N924.67 by the end of 2023. The Naira continued to decline in spite of attempts to stabilize it, including raising the amount of foreign exchange sent to Bureau de Change operators, outlawing cryptocurrencies, and standardizing the exchange rate. By March 2024, the value had dropped to US$/N1505.30. This persistent depreciation has created business uncertainty, leading to the mass exit of multinational companies. The rise of cryptocurrency poses a significant challenge to the monetary authority (Voice of America, 2024).

Aloui et al. (2018) applied the Morlet wavelet technique to explore the relationship between exchange rate and output in Saudi Arabia by considering the effects of oil prices and inflation from 1996 to 2014. The researchers' results showed that oil prices had a negative impact on real output, contributing to the long-term weakening of the Naira. However, the study was conducted in a foreign context with a different methodology.

Yuorkuu et al. (2024) modeled exchange rate volatility using the GARCH (1,1) framework and analyzed its impact on economic growth in Ghana. The study findings indicated that exchange rate volatility negatively affects economic growth in Ghana. However, the current study differs in methodology and location.

Numerous studies in Nigeria have examined exchange rate fluctuations using various methodologies, yielding different findings and conclusions. For instance, Akintunde and Ampitan (2024) forecasted Nigeria's foreign exchange rate dynamics by analyzing time series data on the monthly official exchange rate between the Nigerian Naira and the US Dollar. Based on diagnostic evaluations, the ARIMA (0, 1, 2) model was identified as the most appropriate, according to the Akaike Information Criterion (AIC). Their projections indicated a consistent revaluation of the Naira in future exchange rate trends.

A study from Yola et al. (2021) used Nigeria‟s monthly data from 1981:M1 to 2018:M12 sourced from the Central Bank of Nigeria (CBN) Statistical Bulletin. The data was analyzed using seasonal ARIMA model (SARIMA) which is an extension of Autoregressive (AR) and moving average (MA) process in the popular Box-Jenkins methodology. With 456 data points, the study developed SARIMA (0,1,1) (1,1,1)12 from among the competing models based on its AIC and BIC values. The study predicted the unfavorable value of Naira along seasonal path and thus recommended that appropriate authorities should consider the seasonal component in designing monetary policies targeted at foreign exchange to stabilize the economy.

Henry et al. (2020) examined exchange rate fluctuation and economic growth in Nigeria, using the least square technique on annual frequency on inflation, exchange rate, public debt and from 1997 and 2017. The study reported a negative response of growth to exchange rate depreciation.

Zoramawa et al. (2020) adopted the Johansen co-integration and error correction model to study the exchange rate dynamics and output for the period spanning 1980 to 2019. The Exchange rate stability during the period enhanced economic growth but trade openness was a threat to sustaining the growth path. The study utilized the Johansen cointegration and error correction model to study the exchange rate dynamics. The study differs in timeframe and methodology as well. Based on the backdrop this study aims at forecasting the fluctuation of Nigeria foreign exchange using ARIMA model.

3.0 Methodology

The data used in this study is secondary data sourced from the Central Bank of Nigeria's website. The data covered the period from January 2009 to May 2024. The linear forecast methods employed is Autoregressive Integrated Moving Average (ARIMA) and the Akaike Information Criterion corrected (AICC) is used in selecting the best ARIMA method among other competing ARIMA methods. The analysis was conducted using R statistical software.

3.1 Autoregressive Integrated Moving Average (ARIMA) Method

ARIMA model is a mathematical model of persistence in time series used to uncover the hidden patterns in the data and to generate forecasts and predict a variable’s future values from its past values.. It is a combination of AR (Autoregressive) process, I (Integrated), and MA (Moving Average) process (Box and Jenkins, 1976).

A stationary time series $\{x_t\}$ is said to be an autoregressive process of order p if it satisfies

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} +, \ldots, \phi_p X_p + \varepsilon_t \quad (1)$$

where $\phi_1, \phi_2, \phi_3, ..., \phi_p$ are autoregressive parameters and ε_t is a white noise with mean zero and constant variance, σ^2 .

Equation (1) can be written as:

$(1-\phi_1 B-\phi_2 B^2-...-\phi_p B^p)X_t=\varepsilon_t$. This implies that $\Phi(B)X_t=\varepsilon_t s$, where $\Phi(B)$ is a polynomial in B. For stationarity, the roots of $\Phi(B)$ must lie outside the unit circle $(|B|>1)$.

A stochastic process $\{x_t\}$ is said to be a moving average process (q) if satiafies the difference equation:

$$X_t=\varepsilon_t+\phi_1\varepsilon_{t-1}+\phi_2\varepsilon_{t-2}+,...\phi_p\varepsilon_{t-p}+\varepsilon_t \quad (2)$$

For MA(q), the invertibility condition holds (Shittu and Yaya, 2011).

ARIMA is usually adopted in non-stationary time series (i.e., series that change with respect to time). The ARIMA process is written as

$$Y_t = \text{C} + \phi_1+\phi_2 Y_{t-2}+\ldots,+\phi_p Y_{t-p}+\Theta_1 \mathcal{E}_{t-1}+\Theta_2 \mathcal{E}_{t-2}+\ldots, +\Theta_q \mathcal{E}_{t-q}+\mathcal{E}_t \quad (3)$$

Y_t is the current value of time; C is a constant (intercept) term; $\phi_{1,}\phi_{2,...,}\phi_p$ are coefficient of autoregressive part, indicating the influence of past values; $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p}$; $\Theta_1, \Theta_2, \ldots, \Theta_q$ are the coefficient of the moving average part showing the influence of past errors, $\mathcal{E}_{t-1}, \mathcal{E}_{t-2}, \ldots, \mathcal{E}_{t-q}$ and $\mathcal{E}_t$ is the error term (white noise)

3.2 Stationarity Test

The study employed the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to check for unit roots due to its reliability in determining whether the data is stationary. The test introduced by Kwiatkowski et al. (1992), has a null hypothesis that assumes the data-generating process is stationary. In cases where the data lacks a linear trend, the test follows the specified data-generating process. The KPSS model is presented below.

$$yt = \beta t + rt + \mathcal{E}t \quad (4)$$

where:
yt is the observed time series at time t;

βt is represents a deterministic trend (if present);

rt is a random walk component;

$\mathcal{E}t$ is a stationary error term;

$$KPSS = \frac{1}{T2}\sum_{t=1}^{T} S_t^2/\hat{\sigma}^2 \quad (5)$$

T is the number of observations in the series

S_t is the partial sum of residuals at time t.

$\hat{\sigma}^2$ is an estimate of the variance of the residuals.

3.4 Akaike's Information Criterion (AIC)

The Akaike Information Criterion (AIC) is a measure used to assess the goodness of fit of a statistical model while penalizing for the number of estimated parameters. It helps in model selection by balancing the model's accuracy and complexity (Akaike, 1974) The model for AIC is:

$$AIC = 2k - 2ln(L) \quad (6)$$

where:

k is the number of parameters in the model;
L is the likelihood of the model (or the maximized value of the likelihood function);
In the case of a regression model;
L represents the likelihood of observing the data given the model's parameters. A lower AIC value indicates a better model, as it suggests a model that provides a good fit with fewer parameters.

3.5 The Bayesian Information Criterion (BIC)

The Bayesian Information Criterion (BIC), also known as the Schwarz Information Criterion (SIC) is another criterion used for model selection among a finite set of models. It incorporates a penalty term for the number of parameters, similar to AIC, but with a stronger penalty for complexity (Akaike, 1978). The model for BIC is:

$$BIC = ln(n)k - 2ln(L) \quad (7)$$

where:
n is the number of observations in the dataset.
k is the number of parameters in the model.
L is the likelihood of the model (or the maximized value of the likelihood function).
In general, a lower BIC value indicates a better model, as it balances model fit and complexity, with a stronger emphasis on the number of parameters than AIC.

3.6 Forecast Accuracy Measures

Evaluation of the prediction model is determined by the accuracy of the forecast. Therefore, there are measures for this purpose. They are as follows:

Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|F_t - A_t| \quad (8)$$

where:

n = number of forecasts

F_t = forecasted value

A_t = actual value

Mean Square Error (MSE)

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2 \qquad (9)$$

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2} \qquad (10)$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{F_t - A_t}{A_t}\right| \qquad (11)$$

Mean Forecast Error (MFE)

$$\text{MFE} = \frac{1}{n}\sum_{t=1}^{n}(F_t - A_t) \qquad (12)$$

MASE

$$\text{MASE} = \frac{\frac{1}{n}\sum_{t=1}^{n}|F_t - A_t|}{\frac{1}{n-1}\sum_{t=2}^{n}|F_t - A_{t-1}|} \qquad (13)$$

The above models help in selection of good model for forecasting.

4.0 Results and Discussions

Table 1: Descriptive Statistics for Exchange Rate

Mean	337.5060
Median	359.0000
Maximum	1616.550
Minimum	149.8800
Std. Dev.	234.0865
Skewness	2.795454
Kurtosis	13.47795
Jarque-Bera	1087.227
Probability	0.000000
Sum	62438.61
Sum Square Deviation	10082553
Observations	185

Table 1 provides the descriptive statistics of the variable under review. The descriptive statistics provided summarize the characteristics of the foreign exchange rates in Nigeria over the observed period. The mean value for exchange rate stands at 337.5060. This value represents the average foreign exchange rate over the 185 observations. This indicates that, on average, the exchange rate is approximately 337.51 Naira per unit of foreign currency.

A median of 359.00 suggests that half of the exchange rates are below this value and half are above. This indicates that the distribution may be skewed, as the mean is lower than the median.

The minimum value reflects the lowest recorded exchange rate in the dataset. This suggests that, at its lowest, the exchange rate was approximately 149.88 Naira per unit of foreign currency.

The maximum value for exchange rate is 1616.550. This value shows the highest exchange rate recorded in the dataset, which is significantly higher than both the mean and median. This indicates extreme volatility in the exchange rate.

The standard deviation measures the amount of variation or dispersion in the exchange rates. A standard deviation of 234.09 indicates considerable variability around the mean, confirming the presence of significant fluctuations in the exchange rates.

Skewness indicates the asymmetry of the distribution. A skewness of 2.80 suggests a strong positive skew, meaning that the tail on the right side of the distribution is longer or fatter than the left side. This implies that there are a number of high exchange rate values (outliers) that are pulling the mean higher than the median.

Kurtosis measures the tailedness of the distribution. A kurtosis of 13.48 is significantly higher than the normal distribution value of 3, indicating that the distribution has heavy tails and is peaked. This means there are more extreme values (both high and low) than would be expected in a normal distribution, contributing to the volatility observed.

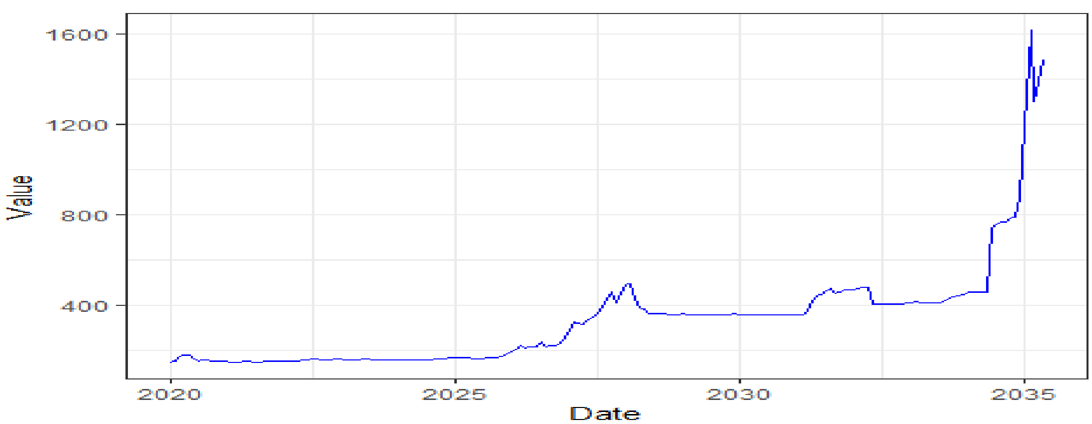

Figure 1: Time Series Plot of Exchange Rate from 2020- 2035

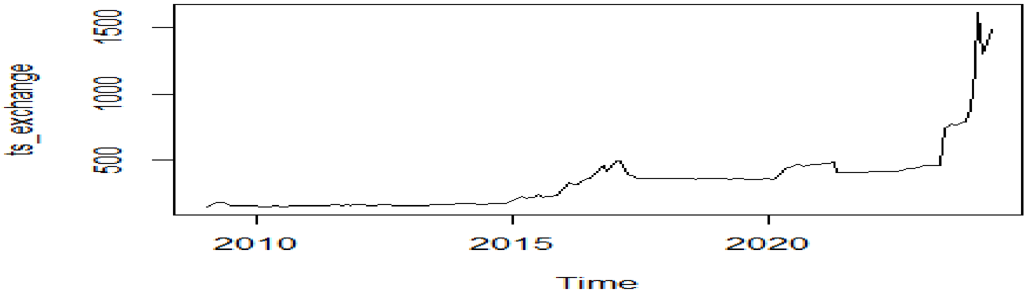

Figure 2: Time Plot of Nigeria Foreign Exchange Rate from January 2009 - May 2024

The time series plot of the Exchange Rate in Figure 1 exhibits trend indicating that the monthly exchange rate is changing over time.

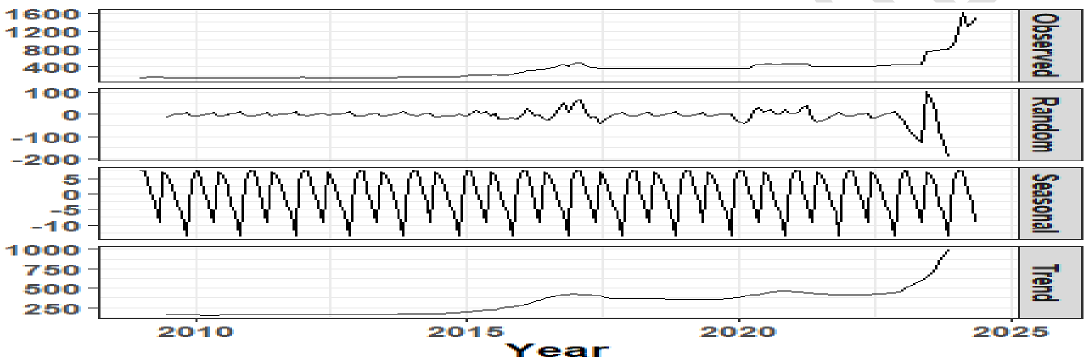

Figure 3: Time Plot of Decomposing Time Series

The Figure 3 above shows the original time series at the top, the estimated component second from the top and third from the top is the seasonal component and the bottom shows the estimated irregular component.

Table 2: KPSS Test of Transformed Exchange Rate

Series	Test	KPPS level	Truncation lag parameter	p-value	Remark
First difference	KPSS	2.4049	4	0.01	Stationary

The KPSS non-stationary test results as displayed in Table 2 show that the transformed Exchange Rate is stationary. The p-value of the KPSS test is less and greater than 0.05. The null hypothesis for the KPSS test is rejected and accepted alternative that there is a stationarity.

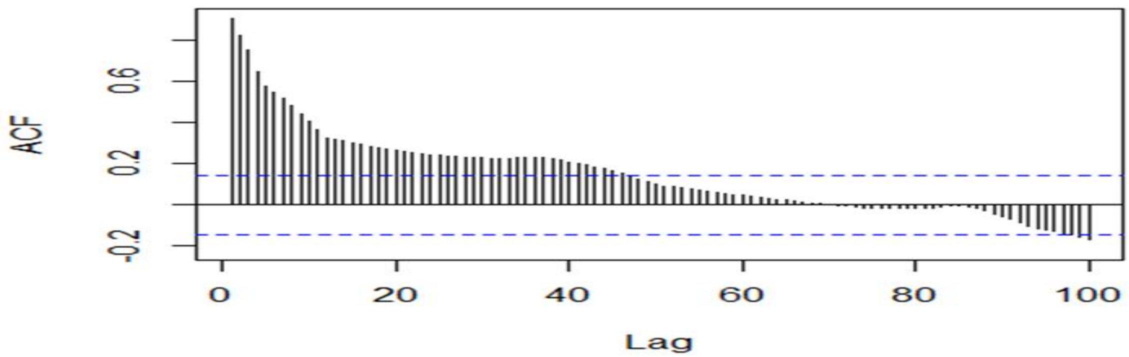

Figure 4: ACF of Original Data of the Exchange Rate

The ACF of the original data in Figure 3 shows a slow decay in the Exchange rate which is evidence of non-stationary series.

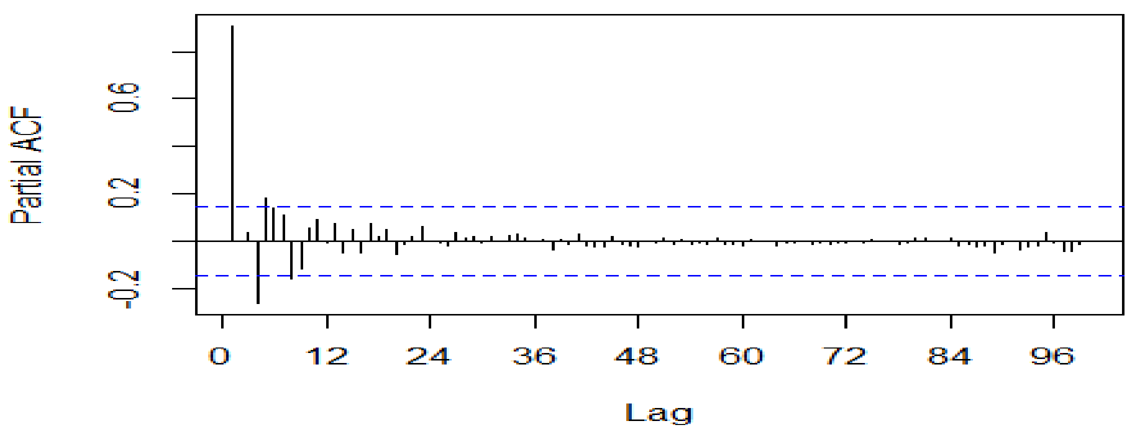

Figure 5: PACF of the Original Data of the Exchange Rate

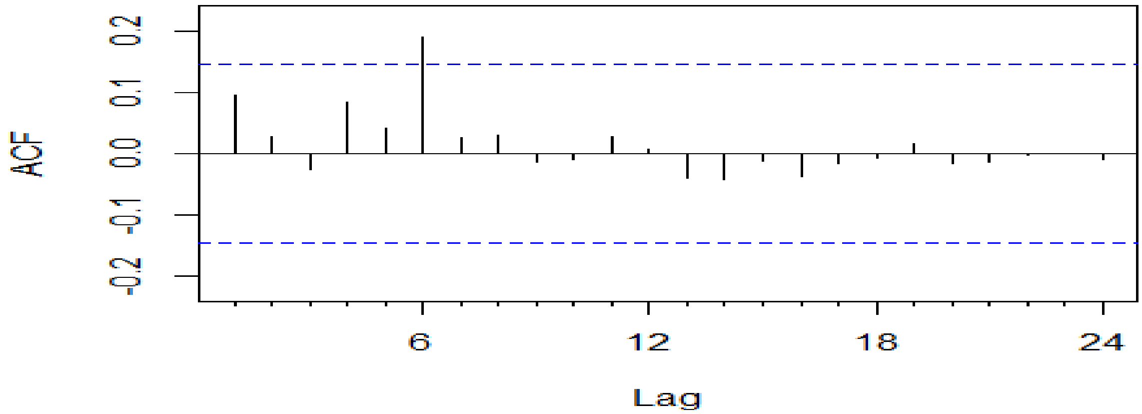

Figure 6: Plot of ACF Trained Stationary Series

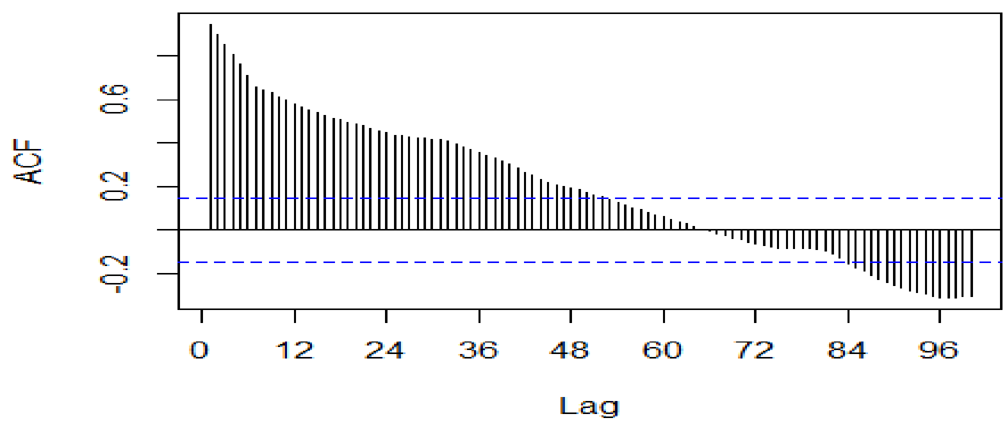

Figure 7: The ACF of the Trained Data showing a Slow Decay in the Exchange Rate Non-Stationary Series.

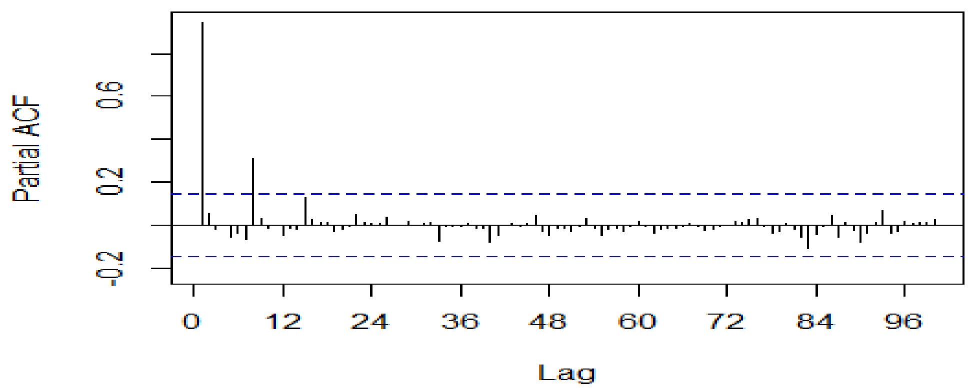

Figure 8: Partial ACF of the Trained Stationary Series.

Table 3: ARIMA Model Selection for USD/ NGN Exchange Rate

MODELS	AIC	BIC
ARIMA(4,2,2)(1,0,1)[12]	1945.93	1974.81
ARIMA(4,2,2)(1,0,0)[12]	1944.1	1969.77
ARIMA(4,2,2)	1942.84	1965.31
ARIMA(4,2,1)(0,0,1)[12]	1966.22	1969.99

Table 3 provides information on the selection of the best model for forecasting the NGN/USD exchange rate, using the Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC) as the evaluation criteria.

ARIMA (4,2,2)(1,0,1)[12] has four autoregressive terms (AR=4), two levels of differencing (I = 2), and two moving average terms (MA=2). This includes a seasonal AR(1) and MA(1) component with a periodicity of 12 months, indicating that seasonal effects are considered in this model.

ARIMA (4,2,2)(1,0,0)[12] is similar to the first, but it only includes a seasonal AR(1) component and omits the seasonal MA(1) term. Its AIC value (1944.1) is slightly lower than the first model, indicating a slightly better fit.

ARIMA (4,2,2) means that the model does not include any seasonal components. It has the lowest AIC value (1942.84) and lowest BIC (1965.31) among the models in the table, indicating that this model provides the best fit to the data compared to the others.

ARIMA (4,2,1)(0,0,1)[12] includes four AR terms, two levels of differencing, and only one MA term, along with a seasonal MA (1) component without any seasonal AR term.

Based on the values of AIC=1942.84 and BIC =1965.31, ARIMA (4, 2, 2) serves as the best fit for forecasting the NGN/USD exchange rate. It has the lowest AIC and BIC value, indicating that it balances model complexity and goodness of fit better than the others.

The equation of the best model is fitted below:

$$Y_t = 0.4474Y_{t-1} - 0.3664Y_{t-2} - 0.0787Y_{t-3} - 0.0787Y_{t-3} - 0.356Y_{t-4} + -1.5943\mathcal{E}_{t-1} + 0.816\mathcal{E}_{t-2}$$

Table 4 Coefficients

	AR(1)	AR(2)	AR(3)	AR(3)	MA(1)	MA(2)
	0.7467	-0.3780	-0.1859	-0.2102	-1.5519	0.7890
Se	0.1303	0.1062	0.1077	0.1119	0.0998	0.0819
sigma^2= 2236						

Table 4 shows that previous value of the exchange rate (Y_{t-1}) has a considerable positive correlation (Y_{t-1}=0.7467; AR1=0.7467) with the present exchange rate (Y_t).
The impacts of subsequent lags (Y_{t-2}, Y_{t-3}, Y_{t-4},) are less and primarily negative, suggesting that their significance decreases with time.

The residual variance (σ^2=2236) suggests unexplained variability, indicating that external factors may also influence exchange rates.

Table 5: Model Residual and Forecast

Months	Forecast points	Lo 80	Hi 80	Lo 95	Hi 95
Jun 2024	1509.352	1448.753	1569.950	1416.674	1602.029
Jul 2024	1739.330	1659.675	1818.985	1617.508	1861.151
Aug 2024	1943.439	1854.772	2032.107	1807.834	2079.045
Sept 2024	2063.271	1963.758	2162.785	1911.078	2215.464
Oct 2024	2163.573	2054.275	2272.871	1996.416	2330.730
Nov 2024	2215.208	2090.265	2340.152	2024.124	2406.293
Dec 2024	2268.063	2117.017	2419.109	2037.058	2499.068
Jan 2025	2370.834	2188.928	2552.740	2092.633	2649.035
Feb 2025	2506.271	2292.626	2719.917	2179.529	2833.014
Mar 2025	2655.263	2411.752	2898.774	2282.845	3027.681
Apr 2025	2793.989	2523.150	3064.828	2379.777	3208.201
May 205	2902.816	2604.820	3200.813	2447.070	3358.563
Jun 2025	2989.334	2661.983	3316.685	2488.694	3489.974
Jul 2025	3072.807	2712.729	3432.884	2522.116	3623.497

Aug 2025	3169.098	2773.120	3565.077	2563.501	3774.695
Sep 2025	3284.639	2851.081	3718.197	2621.569	3947.709
Oct 2025	3412.277	2940.998	3883.555	2691.519	4133.035
Nov 2025	3538.349	3029.765	4046.934	2760.536	4316.162
Dec 2025	3653.211	3107.323	4199.100	2818.347	4488.076
Jan 2026	3755.827	3171.742	4339.913	2862.545	4649.110

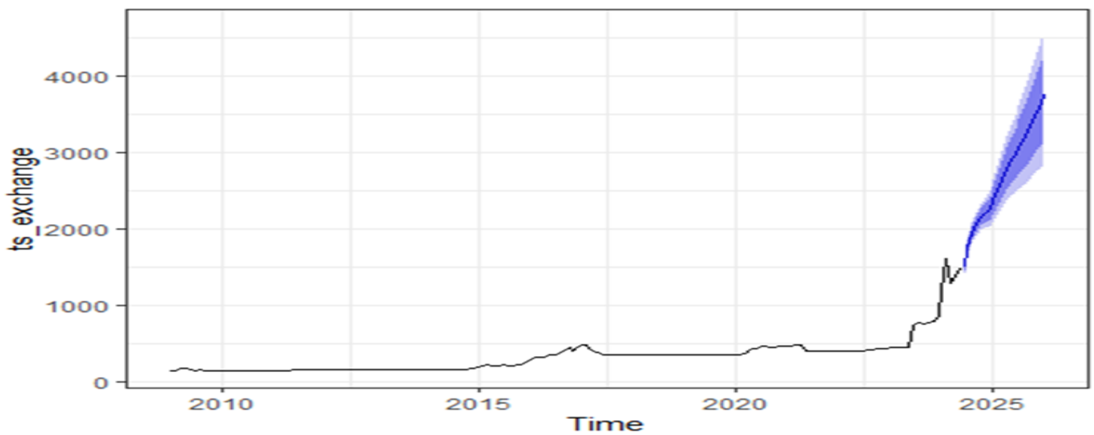

Fig 9: Forecast of Nigeria foreign exchange

In the Figure 9, the two shaded zones of forecast represent the 80% and 95% (lower and upper side) prediction of forecast intervals.

5.0 Conclusion and Recommendations

The ARIMA (4,2,2) model is the best model for forecasting the US Dollar/Nigerian Naira exchange rate over a two-year period, using 15 years of time series data. ARIMA was selected for its capacity to analyze time series data with diverse patterns and autocorrelations between successive values. Statistical tests confirmed that the residuals (forecast errors) from the fitted model were uncorrelated, ensuring the model's reliability.

Furthermore, the ARIMA (4,2,2) model projects a continuous rise in the US Dollar to Naira exchange rate, beginning at 1509.352 in June 2024, increasing to 2370.834 by January 2025, and reaching 3755.827 by January 2026. In light of this predicted decline in the Naira's value, the policymakers are advised to factor these findings into the design of monetary policies aimed at stabilizing the foreign exchange market and the broader economy. While the ARIMA model, like all predictive models, has certain limitations in forecasting precision, it remains widely used for projecting future values in time series data. It is therefore recommended that the ARIMA (4,2,2) model be used for forecasting into future exchange rate of Naira to dollar.

Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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