TIME SERIES MODELING AND FORECASTING OF MONTHLY AVERAGE EXCHANGE RATE OF NIGERIAN-NAIRA AND UNITED STATES-DOLLAR

ABSTRACT

This work considered the time series modeling and forecasting of monthly average exchange rate of the Nigeria -Naria (NGN) and United States -Dollar (USD). The data for this work was obtained from the Central Bank of Nigeria spanning from 2003 to 2024. The time plot of the monthly average exchange rate of both currencies indicated an upward rise in the Dollar and a relatively reduction in the Naira.

To achieve this aim, a powerful timeseries forecasting model known as autoregressive integrated moving average (ARIMA) was employed.

The Exchange rate data was non stationary at level but achieved stationarity after first difference using augmented dickey-fuller (ADF) unit root test via E-views 12.

The strategies for model specification or identification as recommended by Box and Jenkins (1976) were adhered to in this work and ARIMA (8,1,2) was selected as the most parsimonious model among the other five potential or tentative estimated models. This ARIMA (8,1,2) satisfied the residual diagnostic test because of its invertibility and covariance stationary behaviors, this is to say that it had relatively small Akaike's Information Criterion(AIC) and Standard Error of Regression (SER), higher number of Statistically Significant Coefficients and relatively high adjusted R-Squared.

It is hoped that the forecast graph in **figure VIII**of this work would help the Government, Business Operators and Policy makers to invest wisely, plan their budgets, make inform decisions regarding monetary and fiscal policies of the country. The wandering away of the Original Exchange Rate Data from the Forecasted Series stood amazing and a big lesson for Nigerians to strengthen their currency at all cost.

Keywords: Time series, Exchange rate & ARIMA model

1.0 INTRODUCTION

Exchange rate is the rate at which a country's currency is exchanged for other currencies at international market.

Nigeria is characterized by a mixed exchanged rate where Naira (₦) is matched to the US-Dollar (USD) and the rate at which the local currency (Naira) is exchanged for other currencies has noticeable effect on the economy of the country especially for a country like Nigeria that is solely dependent on foreign products.

There was a significant volatility in the exchange rate of Nigeria-Naira and US-Dollar between 2014 to 2024 as a result of economic and political events in both domestic and global levels, this was evident in 2014 oil crash which resulted to a sharp decline in global oil prices and consequently impacted on Nigeria's foreign exchange earnings and spontaneous depreciation of the local currency**(Olomola,2006)** The depreciation of the Naira has a far-reaching effect on Nigeria 's economy such as pushing up inflation, increasing production cost, reducing foreign investment and worsening of the country's debt burden **(Ogochukwu,2016).** The above factors contributed to a higher cost of living of the citizenry, reduced economic growth and limited industrial development which if not put in check would call for a more severe unpalatable effect in the economy of Nigeria **(Ogundipe & Oluwatomisin,2014).**

To curb out these ugly scenarios, a study of this nature is needed to warrant a strategic approach capable of strengthening the indigenous or local production, encouraging diversification and embarking on policy implementation with a view to enhancing the stability of the local currency.

Hence, this study employed a detailed statistical analysis that would reveal the presence of trend (short term or long term) including patterns in the series than a mere observation of the day- to- day changes for a proper comprehension of the dynamics of the exchange rate.

The analysis of the exchange rate's trends and volatility will help in planning and stabilizing macroeconomic components of the county such as the External Reserve, Public Debt, interest rate, unemployment, Gross Domestic Product, Inflation and monetary Policy **(Dahiru & Asemota, 2013).**

The study will help the policy makers to comprehend the underlying trends and factors responsible for fluctuations of the exchange rate in other to aid them in formulating effective monetary and fiscal policies.

The framework of this study is in segments: segment 1.0 is the introductory part, segment 1.1 has a review of related works, segment 2.0 has the methods and materials adopted, segment 2.1shows the working of ARIMA model,3.0 has the assumptions of ARIMA model, 3.1 explains the stages of forecasting using ARIMA while 4.0 has results and lastly segment 4.1& 4.2 cover the discussion, conclusion and possible suggestions.

1.1 RELATED WORK

Many research studies have been done on modelling exchange rate between the Nigeria - Naira and the US - Dollar in the time past. These studies aim at understanding the dynamics of exchange rate fluctuation, identifying the major influencing factors and providing relevant and accurate forecasts. Among the related studies done by other researchers are:

The comparison of autoregressive integrated moving average (ARIMA) model and Artificial Neural Network (ANN) on stock price predictions was done by **(Ayodele, et al 2014)** using New York Stock Exchange (NYSE) and it was observed that ARIMA model's prediction was effective in the short -term with reasonable accuracy than the artificial neural network (ANN).

ARIMA model could handle the inherent seasonality and trends in the exchange rate data, the model faced challenges in predicting the effects of external shock such as global oil price changes which heavily influenced the Nigerian economy **(Adeniran, et al 2014).**

Exchange rate volatility can negatively impact economic growth with ARIMA successfully capturing the short-term fluctuations in the exchange rate data **(Adeniran,et al (2014).**

The autoregressive model integrated moving average (ARIMA) model is a suitable model for exchange rate in short term but the model performance declined with longer-term forecast due to the exchange rate's high volatility **(Adeosun & Gbadamosi, 2022).**

The relationship between the exchange rate macroeconomic variables such as inflation, interest rate and gross domestic product can be obtained using vector autoregressive approach and likewise capturing the interactions between them and Nigerian-Dollar Exchange Rates (**Adeyemi and Alege 2013).**

In a comparison study between VAR model and ARIMA model, inflation and interest rate differentials had significant impacts on the exchange rate and the VAR model captured these interactions better than univariate model like ARIMA (**Adeyemi and Alege 2013).**

The use of generalized autoregressive conditional heteroskedasticity (GARCH) models and autoregressive integrated moving average (ARIMA) in capturing volatility clustering in the Nigerian - Naira to United States' Dollar exchange rate was demonstrated by **Emenike (2010)** with GARCH model being superior in handling volatility clustering in exchange rates and that Naira's volatility was closely tied to external factor like global oil prices.

The performance of autoregressive integrated moving average (ARIMA) and autoregressive fractional moving average (ARFIMA) in modeling the Exchange rate of Nigerian currency to other currencies was carried out in a hybrid study by (**Ayoade, I.A 2024)** with ARFIMA p,fd,q determining the measuring forecast ability for a stationary series that would exhibit features of a long memory properties between the two models. It was noted that ARFIMA was more competent than ARIMA.

The presence of structural breaks in ordinary exchange rate (OER) in Nigeria can be tested using a univariate time series model like ARIMA to explain developments in foreign exchange market

(**John et al, 2017)**.

The impact of exchange rate volatility on non-oil exports in Nigeria using Error Correction model (ECM) with two different measures of volatility; ARCH and TGARCH were assessed by (**Sa'ad et al,2017)** and it was revealed the presence of a significant negative effect on non -oil export performance in Nigeria.

Time series analysis of exchange rate of Nigerian -Naira to United States' Dollar was employed by **Odukoya&Adio(2022)** using ARIMA(1,1,1) as a better forecasting model

ARIMA-GARCH model was also useful in forecasting the exchange rate of Nigerian Naira to US- Dollar both for the emerging and developed countries using a hybrid model with ARIMA (0, I, I) GARCH (1,1) as the best forecast performance model (**Bashir et al,2015)**

Naira appreciated in value when compared to Dollar, Pound and Euro using Euler- Maruyama difference approximation (EMFDA) while interest rate did not have much influence on the value of the exchange rate (**Oyediran et al, 2013)** during the simulation of exchange rates of Nigerian Naira against US- Dollar.

Both symmetric and asymmetric GARCH models such as exponential generalized autoregressive conditional heteroskedasticity (EGARCH) and Threshold generalized autoregressive conditional heteroskedasticity (TGARCH) capture the exchange rate volatility's time -varying nature **(Ogunleye & Adeyeye, 2015).**

Nigerian exchange rate volatility can be examined using two or three distinct regime-switching models in the analysis **(Zira & Adejumo).**

Nigerian -Naira (NGN) depreciated against West African Franc (CFA) during ARIMA intervention modeling of exchange rates of both currencies and monetary policy interventions by central bank had a significant impact on the Naira's exchange rate (**Etuk, et al. 2017a).**

There was an abrupt Jump in the amount of Nigeria -Naira in one unit of Egyptian Pound in August 2017 during an intervention study using ARIMA (**Aboko& Etuk, 2019)**

Central bank should carefully consider both monetary policy and inflation when managing the exchange rate. This will enable them to study the relationship between monetary policy, inflation, and the exchange rate over a long period of time and to provide valuable insights that may not be available for shorter-term studies (**Ette Etuk &IgboyeAboko , 2019).**

2.0 MATERIALS AND METHODS

The work employed a powerful time series forecasting model known as autoregressive integrated moving average (ARIMA) which has been widely used by many time series researchers.

The ARIMA approach which was introduced by Box-Jenkins can also be referred to as Box Jenkins model and consisted of autoregressive term(AR) and moving average term(MA).The 'I' that separates the AR term and MA term indicates the number of times that the series would be integrated to achieve stationarity. Hence the key parameters for anARIMA model are (p, d, q) with' p' denoting a time series that is dependent on past values of itself, 'd' the number of times differencing has to be done to achieve a stationary seriesand 'q' being the past random errors. The strategies for modelling ARIMA include identification stage, estimationstage , diagnostic checking and forecasting stage and these stages were fully adhered in thiswork.

2.1 THE WORKING OF ARIMA MODEL

Autoregressive Integrated Moving Average popularly known as the Box Jenkins (1976) methodology is a method used in forecasting variables using the information obtained from the variables to forecast their trends. This means that the variables are regressed on their own past values.

ARIMA model requires knowing and analyzing the stochastic properties of the variable and it is specifically designed to forecast future movements.

In ARIMA (p, d, q), the AR models are models in which the value of a variable in one period is related to its value in the previous periods. The AR(p) is an autoregressive model with lags:

$Y_t = \mu + \sum_{i=1}^{p} Y_i \, y_{t-1} + \varepsilon_t$ ……………………… (1)

where μ is a constant and y_p is the coefficient for the lagged variable in time $t-p$

AR (1) model is expressed as:

$Y_t = \mu + Y y_{t-1} = \varepsilon_t$………………………………………………………………….. (2)

The MA(q) is the moving average model which accounts for the possibility of a relationship between variable and the residuals from previous periods. It is a moving average model with q lags:

$Y_t = \mu + \mu_t + \theta_i \varepsilon_{t-1}$ ……………………………………………………………….(3)

where θ_q is the coefficient for the lagged error term in time $t-p$

MA (1) model is expressed as: $Y_t = \mu + \varepsilon_t + \theta \varepsilon_{t-1}$……………………………………(4)

An ARIMA (Autoregressive Integrated Moving Average) model is a time series model usually used to predict future values or occurrences based on their past values. ARIMA model generally combines AR (Autoregressive) component, MA (Moving Average) model and,I (the number of differencing done before the series becomes stationary).

Considering an autoregressive model of order p best written as AR(p) and expressed as:

$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t$………………………………… (5)

APPLYING A BACKWARD SHIFT OPERATOR, equation (5) becomes

$$\left(1-\phi_1 B-\phi_2 B^2-\cdots \phi_p B^p\right) Y_t=\varepsilon_t \ldots\ldots\ldots\ldots \text{(6)}$$

A moving average of order q is given by the formular:

$$Y_t= \varepsilon_t+\theta_1 \varepsilon_{t-1}+\theta_2 \varepsilon_{t-2}+\cdots+\theta_q \varepsilon_{t-q} \ldots\ldots\ldots\ldots \text{(7)}$$

If we apply the same backshift operator, then we shall have:

$$\varpi(B)=1+\eta_1 B+\eta_2 B^2+\cdots+\eta_q B^q=0 \ldots\ldots\ldots\ldots \text{(8)}$$

A combination of equations (5) and (6) yields an ARMA (p, q) model as below:

$$Y_t-Y_{t-1}-\phi_2 Y_{t-2}-\cdots-\phi_p Y_{t-p}=\varepsilon_t-\theta_1 \varepsilon_{t-1}-\theta_2 \varepsilon_{t-2}-\cdots-\theta_q \varepsilon_{t-q} \ldots\ldots\ldots\ldots \text{(9)}$$

In the above equations, ε_t denotes a white noise process that is considered as normally distributed with a zero mean and variance (σ^2). We can further express equation (5) as below:

$$\Psi(B) Y_t=\Phi(B) \varepsilon_t \ldots\ldots\ldots\ldots \text{(10)}$$

Where $\Psi(B)=\left(1-\phi_1 B-\phi_2 B^2-\cdots \phi_p B^p\right)$

This makes it easier for ARIMA (p, d, q) to be formulated as below:

$$Y_t= X_t-X_{t-1}=(1-B) X_t \ldots\ldots\ldots\ldots \text{(11)}$$

$$Y_t-Y_{t-1}=X_t-2 X_{t-1}+X_{t-2}=(1-B)^2 X_t \ldots\ldots\ldots\ldots \text{(12)}$$

3.0 THE ASSUMPTIONS OF THE MODEL

The time series data must be stationary for (AR models). A series is said to be stationary if it enables mean reversion, if it has a finite and time-invariant variance and lastly if its theoretical correlogram diminishes as the lag length increases. The invertibility assumption (for MA model) states that the series can be represented by a finite order of MA or convergent autoregressive process, the series can use autoregressive function (ACF) and partial autoregressive function (PACF) for identification and the series can be approximated by autoregressive model.

3.1 THE STAGES OF FORECASTING USING ARIMA MODEL

The Box and Jenkins (1976) methodology identified four steps by which forecasting can be done which include; identification, estimation, Diagnostic Checking and Forecasting

In identification procedure, the autocorrelation function (ACF) and the partial autocorrelation (PACF) known as the correlogram of the series are examined. The ACF reveals the order of the moving average (MA) terms while the PACF reveals the order of the autoregressive (AR) terms.

The ACF helps to understand how each data point in our time series relates to its past values while the lag max parameter specifies the maximum number of time lags to consider.

The PACF indicates the relationship between a data point and its past value while removing the influence of other time lags. Basically, it is the correlation between $Y_t \ and \ Y_{t-k}$ after removing the effect of the intermediate Y's (the marginal impact).

The model Estimation is usually done by ordinary least square (OLS) method. The estimation is done using the stationary specified model. The model with the smallest number of parameters is usually the best to be used for forecasting. this means that parsimonious models give better forecast than over - parameterized model.

In model diagnostic procedure, the correlogram of the tentative best model is checked for any uncaptured information in the model. If all the lags fall within the 95-confidence interval or within the threshold lines (error bands), the model passes the residual diagnostic test.

The forecasting can now be done using the model that satisfied the residual diagnostic test hence the correlogram for the adjusted ARIMA model has to be flat and confirmed by Ljung Box test.

4.0 RESULTS AND DISCUSSIONS

The results of the analysis of this work are presented in tables and figures as indicated below. There are seven tables and eight figures as presented below for clarity purpose.

TABLE 1: ESTIMATION OF ARIMA (1,1,1)

Dependent Variable: D(EXCHANGE_RATE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/07/25 Time: 10:15
Sample: 2003M02 2024M12
Included observations: 263
Convergence achieved after 104 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.309870	4.458553	1.190940	0.2348
AR(1)	-0.494913	0.058911	-8.401068	0.0000
MA(1)	0.768714	0.048719	15.77843	0.0000
SIGMASQ	1700.498	48.95067	34.73902	0.0000

R-squared	0.083937	Mean dependent var	5.449430
Adjusted R-squared	0.073326	S.D. dependent var	43.16707
S.E. of regression	41.55431	Akaike info criterion	10.30780
Sum squared resid	447231.0	Schwarz criterion	10.36213
Log likelihood	-1351.475	Hannan-Quinn criter.	10.32963
F-statistic	7.910527	Durbin-Watson stat	2.070111
Prob(F-statistic)	0.000046		

Inverted AR Roots	-.49
Inverted MA Roots	-.77

TABLE 2: ESTIMATION OF ARIMA (2,1,2)

Dependent Variable: D(EXCHANGE_RATE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/07/25 Time: 10:23
Sample: 2003M02 2024M12
Included observations: 263
Convergence achieved after 159 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.544323	5.232529	1.059588	0.2903
AR(2)	-0.855228	0.069278	-12.34491	0.0000
MA(2)	0.703710	0.077959	9.026715	0.0000
SIGMASQ	1728.591	57.63194	29.99363	0.0000

R-squared	0.068803	Mean dependent var	5.449430
Adjusted R-squared	0.058017	S.D. dependent var	43.16707
S.E. of regression	41.89615	Akaike info criterion	10.32455
Sum squared resid	454619.5	Schwarz criterion	10.37888
Log likelihood	-1353.678	Hannan-Quinn criter.	10.34638
F-statistic	6.378884	Durbin-Watson stat	1.688779
Prob(F-statistic)	0.000347		

Inverted AR Roots	-.00+.92i	-.00-.92i
Inverted MA Roots	-.00+.84i	-.00-.84i

TABLE 3: ESTIMATION OF ARIMA (3,1,3)

Dependent Variable: D(EXCHANGE_RATE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/07/25 Time: 10:29
Sample: 2003M02 2024M12
Included observations: 263
Convergence achieved after 76 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.392766	5.083356	1.060867	0.2897
AR(3)	0.210618	0.661738	0.318280	0.7505
MA(3)	-0.078489	0.653968	-0.120020	0.9046
SIGMASQ	1823.164	43.29361	42.11162	0.0000

R-squared	0.017856	Mean dependent var	5.449430
Adjusted R-squared	0.006480	S.D. dependent var	43.16707
S.E. of regression	43.02698	Akaike info criterion	10.37683
Sum squared resid	479492.1	Schwarz criterion	10.43116
Log likelihood	-1360.553	Hannan-Quinn criter.	10.39867
F-statistic	1.569630	Durbin-Watson stat	1.720007
Prob(F-statistic)	0.197154		

Inverted AR Roots	.59	-.30-.52i	-.30+.52i
Inverted MA Roots	.43	-.21+.37i	-.21-.37i

TABLE 4: ESTIMATION OF ARIMA (1,1,3)

Dependent Variable: D(EXCHANGE_RATE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/07/25 Time: 10:37
Sample: 2003M02 2024M12
Included observations: 263
Convergence achieved after 118 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.300933	6.228846	0.851030	0.3955
AR(1)	0.137914	0.034354	4.014468	0.0001
MA(3)	0.145265	0.028701	5.061310	0.0000
SIGMASQ	1793.070	30.53204	58.72750	0.0000

R-squared	0.034068	Mean dependent var	5.449430
Adjusted R-squared	0.022880	S.D. dependent var	43.16707
S.E. of regression	42.67039	Akaike info criterion	10.36030
Sum squared resid	471577.5	Schwarz criterion	10.41463
Log likelihood	-1358.379	Hannan-Quinn criter.	10.38213
F-statistic	3.044936	Durbin-Watson stat	1.889811
Prob(F-statistic)	0.029362		

Inverted AR Roots	.14		
Inverted MA Roots	.26-.46i	.26+.46i	-.53

TABLE 5: ESTIMATION OF ARIMA (1,1,8)

Dependent Variable: D(EXCHANGE_RATE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/07/25 Time: 11:04
Sample: 2003M02 2024M12
Included observations: 263
Convergence achieved after 141 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.628698	4.633222	1.214856	0.2255
AR(1)	0.088575	0.022019	4.022641	0.0001
MA(8)	0.342966	0.028162	12.17834	0.0000
SIGMASQ	1666.747	33.83501	49.26103	0.0000

R-squared	0.102119	Mean dependent var	5.449430
Adjusted R-squared	0.091718	S.D. dependent var	43.16707
S.E. of regression	41.13986	Akaike info criterion	10.29076
Sum squared resid	438354.5	Schwarz criterion	10.34509
Log likelihood	-1349.235	Hannan-Quinn criter.	10.31259
F-statistic	9.818933	Durbin-Watson stat	1.951856
Prob(F-statistic)	0.000004		

Inverted AR Roots	.09			
Inverted MA Roots	.81-.33i	.81+.33i	.33+.81i	.33-.81i
	-.33+.81i	-.33-.81i	-.81-.33i	-.81+.33i

TABLE 6: ESTIMATION OF ARIMA (8,1,2)

Dependent Variable: D(EXCHANGE_RATE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/09/25 Time: 10:41
Sample: 2003M02 2024M12
Included observations: 263
Convergence achieved after 164 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.979039	6.249366	0.956743	0.3396
AR(8)	0.332846	0.021901	15.19770	0.0000
MA(2)	-0.204073	0.023701	-8.610246	0.0000
SIGMASQ	1604.855	42.21892	38.01271	0.0000

R-squared	0.135460	Mean dependent var	5.449430
Adjusted R-squared	0.125446	S.D. dependent var	43.16707
S.E. of regression	40.36881	Akaike info criterion	10.25297
Sum squared resid	422077.0	Schwarz criterion	10.30730
Log likelihood	-1344.266	Hannan-Quinn criter.	10.27480
F-statistic	13.52707	Durbin-Watson stat	1.690102
Prob(F-statistic)	0.000000		

Inverted AR Roots	.87	.62-.62i	.62+.62i	-.00-.87i
	-.00+.87i	-.62+.62i	-.62+.62i	-.87
Inverted MA Roots	.45	-.45		

Having estimated all the six possible tentative models as presented above, a summary statistic table was then prepared showing their **Sigma Values(volatility levels), Adjusted Residual Squared values,Significance Coefficient Values and lastly their Akaike's Information Criteria Values**. The reason for the summary statistic table was to pick the most appropriate or parsimonious model by comparing theirvalues as indicated above.

CRITERIA FOR APPROPRIATE MODEL SELECTION ARE:

The model must have significant coefficients (its coefficients must be statistically significant)

The model must have the highest adjusted r-squared value compared with others

The model must have the least volatility value

The model must have the lowest AIC or SIC value.

By inspecting the summary statistic table below, ARIMA (8,1,2) was chosen as the most appropriate model (the model that met the criteria above).

TABLE 7: SUMMARY STATISTIC TABLE OF THE SIX TENTATIVE MODELS

TENTATIVE MODELS	ARIMA (1,1,1)	ARIMA (2,1,2)	ARIMA (3,1,3)	ARIMA (1,1,3)	ARIMA (1,1,8)	ARIMA (8,1,2)
SIGMA	1700.498	1728.591	1823.164	1793.070	1666.747	1604.855
C	3	3	1	3	3	3
ADJ.R-SQ.	0.073326	0.058017	0.006480	0.022880	0.091718	0.125446
AIC	10.30780	10.32455	10.37683	10.36030	10.29076	10.25297

The relevant figures for this work are eight in number and are presented below:

FIGURE 1: TIME PLOT OF NAIRA -DOLLAR EXCHANGE RATE

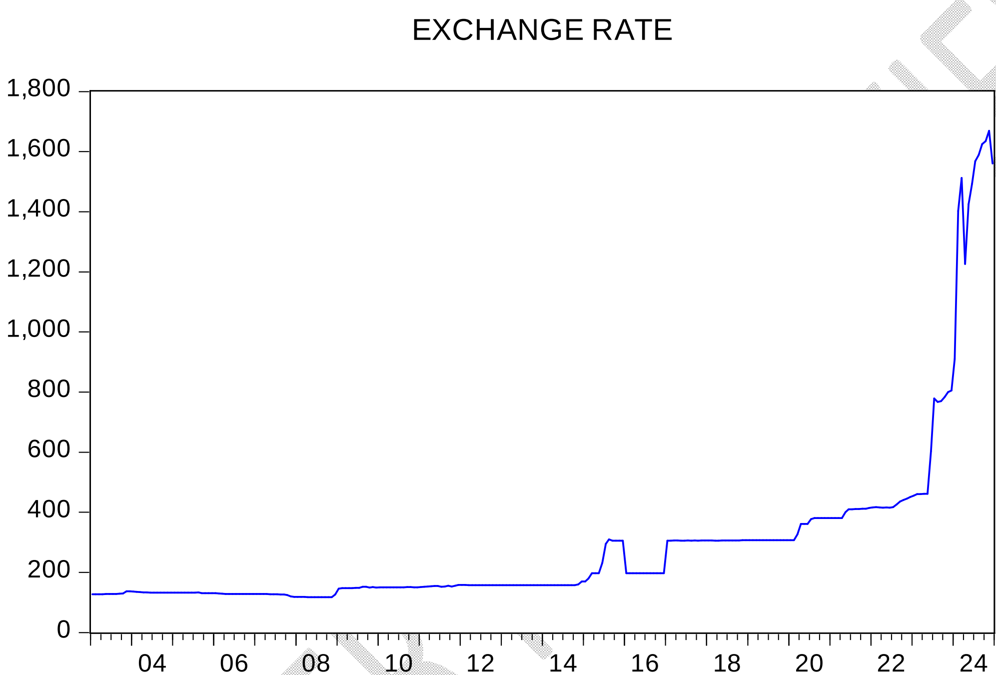


FIGURE 2: PLOT OF DIFFERENCED SERIES

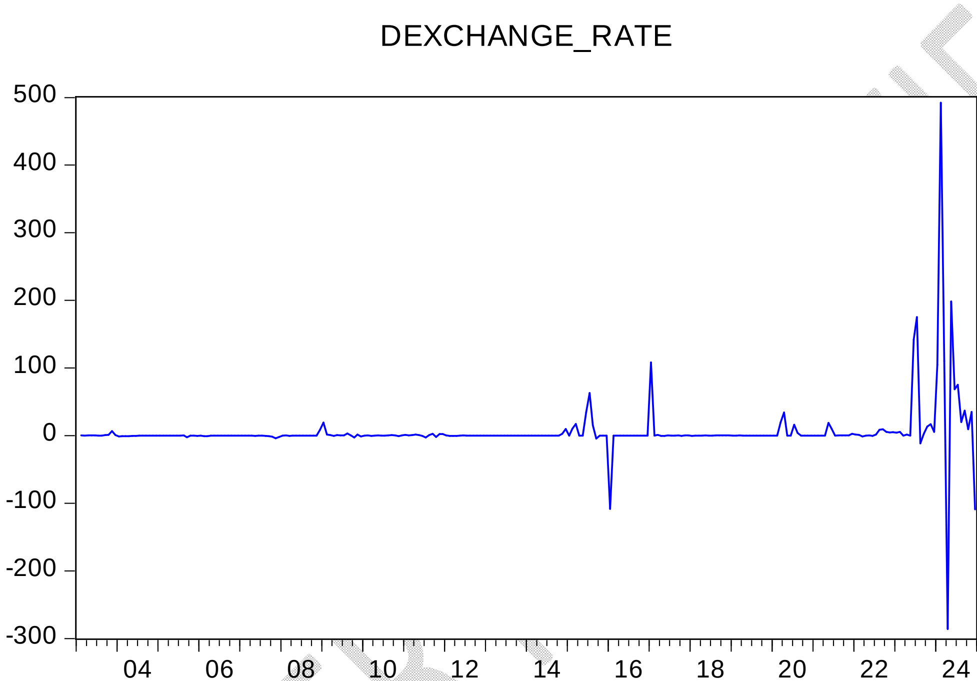
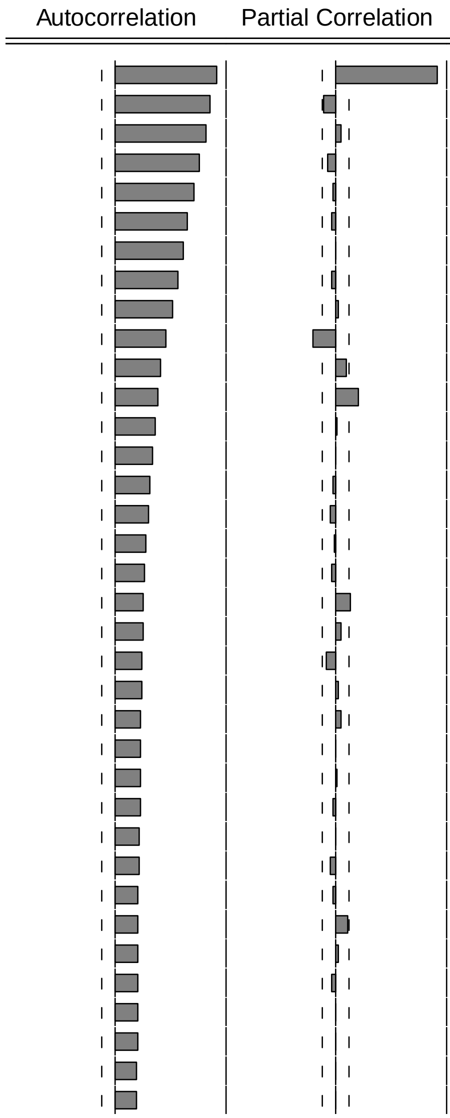


FIGURE 3: CORRELOGRAM OF SERIES AT LEVELS



	AC	PAC	Q-Stat	Prob
1	0.953	0.953	242.42	0.000
2	0.897	-0.121	457.96	0.000
3	0.847	0.051	651.06	0.000
4	0.795	-0.071	821.75	0.000
5	0.741	-0.033	970.73	0.000
6	0.687	-0.038	1099.3	0.000
7	0.636	0.002	1209.8	0.000
8	0.585	-0.041	1303.7	0.000
9	0.539	0.029	1383.6	0.000
10	0.477	-0.211	1446.6	0.000
11	0.425	0.106	1496.6	0.000
12	0.398	0.208	1540.8	0.000
13	0.377	0.009	1580.7	0.000
14	0.356	-0.006	1616.2	0.000
15	0.335	-0.024	1647.8	0.000
16	0.314	-0.042	1675.7	0.000
17	0.293	-0.009	1700.0	0.000
18	0.271	-0.036	1721.0	0.000
19	0.260	0.140	1740.3	0.000
20	0.256	0.047	1759.1	0.000
21	0.252	-0.097	1777.4	0.000
22	0.248	0.032	1795.2	0.000
23	0.243	0.051	1812.4	0.000
24	0.239	0.007	1829.2	0.000
25	0.235	0.011	1845.5	0.000
26	0.232	-0.018	1861.3	0.000
27	0.228	0.005	1876.7	0.000
28	0.224	-0.048	1891.6	0.000
29	0.221	-0.018	1906.3	0.000
30	0.219	0.109	1920.6	0.000
31	0.216	0.029	1934.7	0.000
32	0.214	-0.037	1948.5	0.000
33	0.211	0.001	1962.0	0.000
34	0.207	-0.004	1975.1	0.000
35	0.204	0.006	1987.8	0.000
36	0.200	-0.004	2000.2	0.000

FIGURE 4: CORRELOGRAM OF D(EXCHANGE- RATE)

Date: 01/07/25   Time: 09:52
Sample: 2003M01 2024M12
Included observations: 263

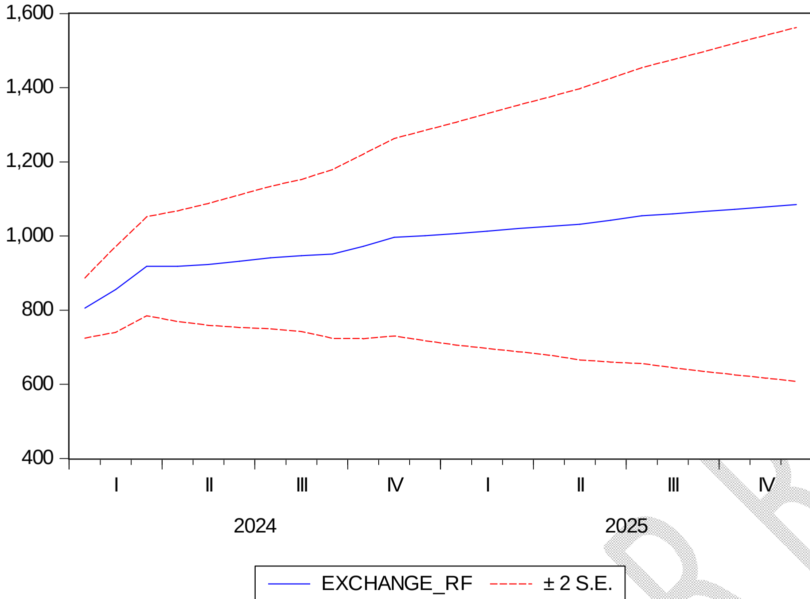
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.113	0.113	3.3905	0.066
		2	-0.229	-0.245	17.392	0.000
		3	0.131	0.205	21.979	0.000
		4	0.149	0.043	27.925	0.000
		5	0.053	0.114	28.691	0.000
		6	0.040	0.041	29.132	0.000
		7	0.173	0.187	37.245	0.000
		8	0.276	0.248	58.067	0.000
		9	-0.070	-0.099	59.421	0.000
		10	-0.124	-0.038	63.667	0.000
		11	0.053	-0.102	64.442	0.000
		12	0.021	-0.082	64.561	0.000
		13	0.024	-0.002	64.724	0.000
		14	0.013	-0.053	64.775	0.000
		15	0.013	-0.015	64.819	0.000
		16	0.017	-0.020	64.905	0.000
		17	-0.019	0.071	65.010	0.000
		18	-0.011	0.047	65.043	0.000
		19	0.007	0.022	65.056	0.000
		20	-0.003	0.013	65.059	0.000
		21	0.002	-0.022	65.060	0.000
		22	0.002	0.003	65.062	0.000
		23	-0.002	-0.013	65.063	0.000
		24	0.000	-0.014	65.063	0.000
		25	0.010	-0.004	65.093	0.000
		26	0.004	-0.008	65.098	0.000
		27	-0.006	0.010	65.109	0.000
		28	-0.006	-0.000	65.119	0.000
		29	-0.002	0.004	65.120	0.000
		30	-0.002	-0.006	65.121	0.000
		31	-0.002	-0.003	65.122	0.000
		32	0.010	0.012	65.153	0.000
		33	0.018	0.013	65.246	0.001
		34	-0.005	-0.001	65.255	0.001
		35	-0.006	0.005	65.266	0.001
		36	0.009	0.007	65.292	0.002

FIGURE 5: CORRELOGRAM OF THE SELECTED MODEL

Date: 01/09/25 Time: 11:02
Sample: 2003M01 2024M12
Included observations: 263
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.152	0.152	6.1452	
		2	-0.036	-0.060	6.4908	
		3	0.139	0.158	11.683	0.001
		4	0.133	0.087	16.448	0.000
		5	0.064	0.049	17.558	0.001
		6	0.170	0.155	25.353	0.000
		7	0.174	0.113	33.638	0.000
		8	0.026	-0.015	33.829	0.000
		9	-0.103	-0.145	36.746	0.000
		10	-0.043	-0.092	37.266	0.000
		11	0.058	0.010	38.198	0.000
		12	0.015	-0.013	38.264	0.000
		13	0.032	0.040	38.541	0.000
		14	0.007	-0.003	38.555	0.000
		15	-0.051	-0.010	39.291	0.000
		16	-0.046	0.008	39.882	0.000
		17	-0.005	-0.001	39.888	0.000
		18	0.013	-0.006	39.935	0.001
		19	0.014	-0.002	39.990	0.001
		20	0.012	0.015	40.029	0.002
		21	0.004	0.021	40.033	0.003
		22	0.004	0.026	40.038	0.005
		23	-0.002	0.002	40.039	0.007
		24	-0.004	-0.022	40.043	0.011
		25	0.000	-0.021	40.043	0.015
		26	-0.002	-0.019	40.045	0.021
		27	-0.007	-0.013	40.058	0.029
		28	-0.009	-0.008	40.085	0.038
		29	-0.003	0.006	40.087	0.050
		30	-0.008	0.004	40.106	0.065
		31	-0.007	0.010	40.119	0.082
		32	0.008	0.019	40.139	0.102
		33	0.016	0.018	40.218	0.124
		34	-0.007	-0.009	40.233	0.151
		35	-0.007	-0.007	40.248	0.180
		36	0.012	0.006	40.293	0.212

FIGURE 6 :GRAPH OF THE FORECASTED VALUES



Forecast: EXCHANGE_RF	
Actual: EXCHANGE_RATE	
Forecast sample: 2024M01 2025M12	
Included observations: 24	
Root Mean Squared Error	561.7714
Mean Absolute Error	537.7244
Mean Abs. Percent Error	35.51404
Theil Inequality Coefficient	0.232746
Bias Proportion	0.916221
Variance Proportion	0.073555
Covariance Proportion	0.010225
Theil U2 Coefficient	2.248130
Symmetric MAPE	43.75703

FIGURE 7: CONFIRMATION OF INVERTIBILITY AND COVARIANCE STATIONARY PROPERTY.

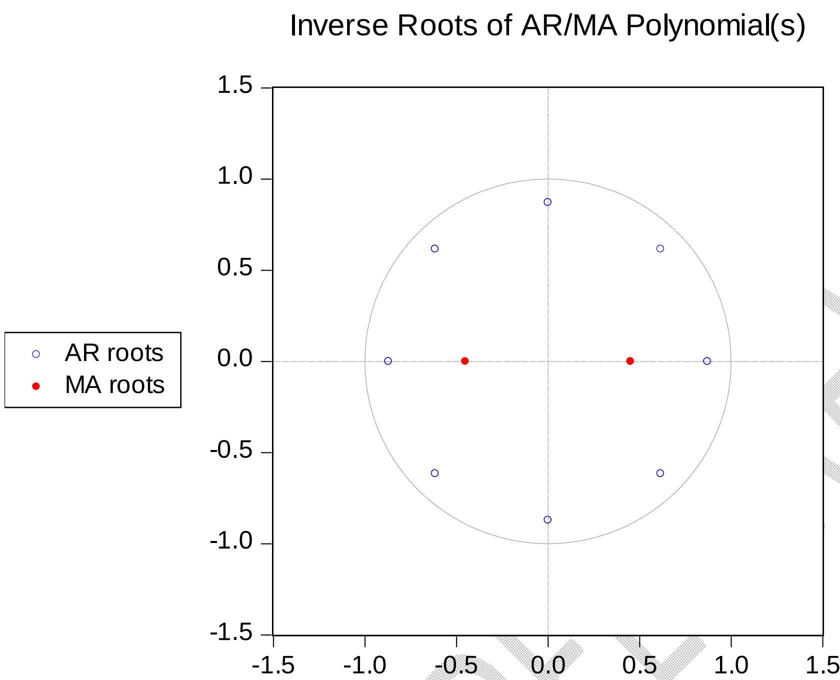
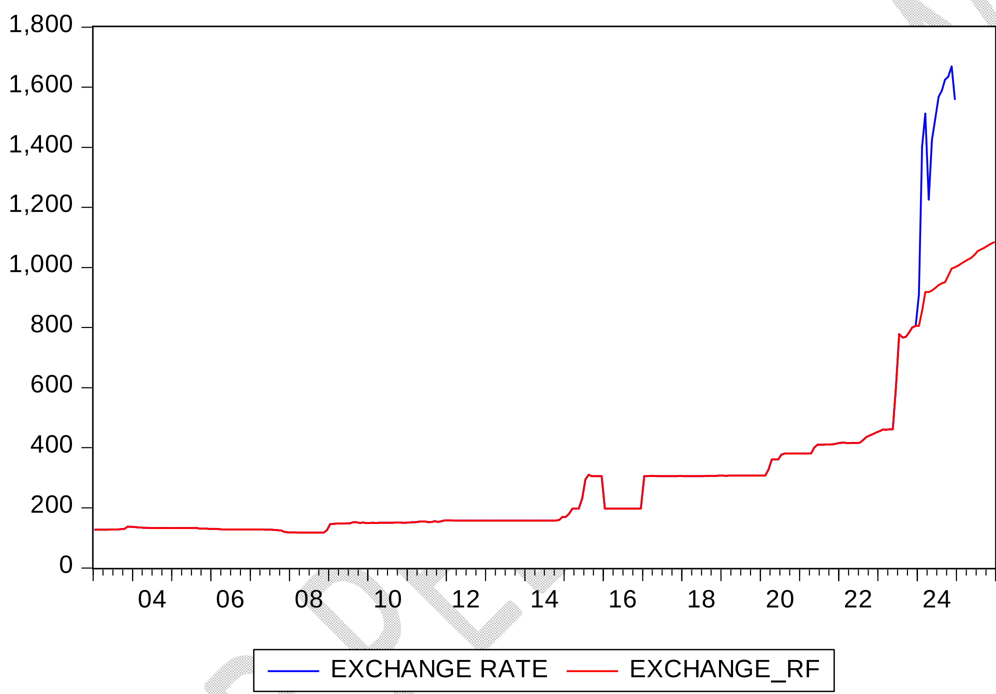


FIGURE 8:GRAPH OF THE FORECASTED VALUES AGAINGST THE ACTUAL



4.1 DISCUSSION

The time plot of the series in figure one showed a relatively steady rate until 2015 till 2024 when it showed an upward trend and could not revert to its mean indicating nonstationary behavior but later achieved stationarity after one time differencing. The **correlogram of the series at ' level' and first difference were taken as represented in figures three & four** respectively . The correlogram of a nonstationary series in **figure three** showed an ACF that died out gradually while that of a stationary series in **figure four** decayed rapidly from its initial value. The time plot of the differenced series was taken as shown in **figure two**, followed by model identification procedures as specified by Box and Jenkins. Six possible tentative models were estimated and the most parsimonious one was considered as the best forecasting power and subsequently used in the forecasting.

From summary statistics table above the most parsimonious model was ARIMA (8,1,2) was highlighted in red because it had the lowest volatility, highest adjusted R-value, least Akaike's information criteria with three of its coefficients statistically significant.

A visual inspection of **figure one** showed that the time plot of the average exchange rate of NGN - US-Dollar had an upward trend and a time varying variance making the series nonstationary as was also confirmed by the correlogram of the series at level in **figure three**but after a one time differencing the series became stationary as shown in the correlogram in **figure four**, so the correlogram of the stationary structure was used to identify the AR and MA components. The PACF was used to determine the AR orders while the ACF was used to determine the MA orders. After ensuring stationary behavior of the series, the model was specified as revealed in **figure four** and estimated accordingly in tables 1,2,3,45 &6. The most parsimonious model ARIMA (8,1,2) was selected but residual diagnostic test showed that there was some uncaptured informationin lags 16 for both AR and MA terms because the bars were exactly on threshold lines suggesting ARIMA (16,1,16) but after estimating ARIMA(16,1,16), the result still presented ARIMA(8,1,2) as the chosen model as shown in the summary statistic in table seven above ; with the least AIC, lowest SIGMA(volatility), highest Adjusted R-Squared value and three of its coefficients statistically significant.

ARIMA (8,1,2) had the better forecasting power thus was used in the forecast equation as the best model among the five other tentative models.

The graph of the forecasted values against the actual values in **figureeight** showed that from December 2023 the until December 2024 the Naira to Dollar average exchange rate took a different dimension. This was reflected in the wandering away of the blue line in the graph but the forecasted values with red line maintained its upward trend indicating that the Naira to Dollar exchange rate will not vary so much (it will maintain the trend) in 2025.

4.2 CONCLUSION

This work had allowed for a detailed statistical analysis revealing the presence of trend and patterns in the series and capable of giving proper comprehension of the dynamics of exchange rate. The work also analyzed the exchange rate's volatility which will help in stabilizing macroeconomic components of Nigeria. However, we recommend future research to base on hybrid model where ARIMA model can be combined with other forecasting models. We advise that businessmen, Policy makers and Government bodies to take advantage of the forecast and plan.We also suggest an urgent intervention by the Nigerian government towards improving the performance of the local currency (Naira) in the foreign exchange market since it is hoped to boost or ignite a favorable market for the potential investors. The Central Bank of Nigeria's Monetary Policies and InterestRatesDecisions should aggressively be reshaped based on the findings of this work in the forecast graph.

COMPETING INTERESTS DISCLAIMER:

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

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Details of the AI usage are given below:

1.

2.

3.

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