Modelling Dollar-Naira Exchange Rate In Nigeria

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Abstract—This paper presents an empirical study of modelling and forecasting time series data of the official Exchange rate of Nigeria. The Box-Jenkins ARIMA methodology was used for forecasting the yearly data collected from 1972 to 2017. Result of the analysis revealed that the series became stationary at first difference. The diagnostic checking has shown that ARIMA (0, 1, 0) is appropriate or optimal model based on the Log-likelihood (LogLik), Akaike's Information Criterion (AIC),andthe Bayesian Information Criterion (BIC). The performance of `auto.arima` function in R gives the best model for exchange of dollar to Naira without the rigours of testing for other ARIMA models. With Minimum Mean Error (ME), Mean Percentage Error (MPE), and Root Mean Squared Error (RMSE), which proves that ARIMA (0, 1, 0) model is the best or optimal model for the period forecasted at 5% level of significance. The upward movement in the forecasts of the exchange rate would be helpful for policy makers in Nigeria.

Keywords--*ARIMA, exchange rate, Optimal model, selection criteria.*

I. Introduction

Most researchers have done a great research on forecasting of exchange rate for developed and developing countries using different approaches. The approach might vary in either fundamental or technical approach. Like the work of Harrison (1998), used a technical approach to forecast Nigeria naira – US dollar using seasonal ARIMA model for the period of 2004 to 2011. He reveals that the series (exchange rate) has a negative trend between 2004 and 2007 and was stable in 2008. Newaz (2008) made a comparison on the performance of time series models for forecasting exchange rate for the period of 1985 – 2006. He compared ARIMA model, NAÏVE 1, NAÏVE 2 and exponential smoothing techniques to see which one fits the forecasts of exchange rate. He reveals that ARIMA model provides a better forecasting of exchange rate than either of the other techniques; selection was based on MAE (mean absolute error), MAPE (mean absolute percentage error), MSE (mean square error), and RMSE (root mean square error).

Further work, Shittu and Olaoluwa (2008) try to measure the forecast performance of ARMA and ARFIMA model on the application to US/UK pounds foreign exchange. They reveal that ARFIMA model was found to be better than ARMA model as indicates by the measurement criteria. Their persistent result reveals that ARFIMA model is more realistic and closely reflects the current economic reality in the two countries which was indicated by their forecasting evaluation tool. They found out that their result was in conformance with the work of Kwiatkowski et al (1992).

Shittu (2008) used an intervention analysis to model Nigeria exchange rate in the presence of financial and political instability from the period (1970-2004). He explains that modeling of such series using the technique was misleading and forecast from such model will be unrealistic, he continued in his findings that the intervention are pulse function with gradual and linear but significant impact in the naira – dollar exchange rates.

Appiah and Adetunde (2011) conducted a research on forecasting exchange rate between the Ghana cedi's and the US dollar using time series analysis for the period January 1994 to December 2010. Their findings reveal that predicted rates were consistent with the depreciating trend of the observed series and ARIMA (1, 1, 1) was found to be the best model to such series and a forecast for two years were made from January 2011 to December 2012 and reveals that a depreciation of Ghana cedi's against the US dollar was found.

The literature is growing in recent times on the examination of the distributional properties of exchange rates and its links to the behavior of private domestic investment. Thomas, (1997) in his study of 86 developing countries examined data on terms of trade, real exchange rates, and property rights and concluded that while factors including credit, availability and the quality of physical and human infrastructure are important influences, uncertainty in the foreign exchange rate was negatively related to private investment in sub-Saharan countries. Employing the variability in real exchange rates as an explanatory variable in regression analysis, Jayaraman

(1996) in his cross-country study on the macroeconomic environment and private investment in six Pacific Island countries observed a statistically significant negative relationship between the variability in the real exchange rate and private investment.

Duncan *et al*. (1999) commented that although variability in the real exchange rate is a reasonable proxy for instability in major economic variables as fluctuations in inflation and productivity and more generally in fiscal and monetary management are reflected in the real exchange rate, it is not a good measure of the uncertainty attached to policy or the insecurity of property rights and enforcement of contracts or the level of corruption.

Observing that these non-economic factors appear to be very significant influences on investment in the Pacific Island countries, Duncan *et al.* 1999, however, concede that no quantitative or qualitative evidence is available of their size or their impact. In the absence of such evidence, any study on private investment is to be necessarily restricted to the conventional variables ARIMA models have been used for forecasting different types of time series and have been compared with a benchmark model for its validity. Therefore, to capture the long term trend, many authors had used Auto regressive Integrated Moving Average (ARIMA) model as proposed by Box-Jenkins (1976), to forecast the exchange rate. The essence of this approach was that the data were used for identifying the estimation of the random components in the form of moving average and autoregressive process. It did not identify and measure the structural relationship as was attempted when forecasting with econometric models. They used exponential smoothing to forecast yields in United States and Canada. They also compared the forecasting accuracy between parametric modeling and exponential smoothing.

Yinusa (2008) investigated the relationship between nominal exchange rate volatility and dollarization in Nigeria by applying Granger causality test for the period 1986–2003 using quarterly data. The study reported a bi-causality between them but the causality from dollarization to exchange rate volatility appears stronger and dominates. He however concluded that policies that aim to reduce exchange rate volatility in Nigeria must include measures that specifically address the issue of dollarization. But, the exact measure of exchange rate volatility in the study was not reported.

In the same vein, Ogunleye (2009) investigated the relationship between exchange rate volatility and Foreign Direct Investments (FDI) inflows in Sub- Saharan Africa using Nigeria and South Africa as case studies. By endogeneizing exchange rate volatility, the study uses a two – stage Least Squares methodology. The study finds that in Nigeria, there is a statistically significant relationship between the variables, with exchange rate volatility retarding FDI inflows and FDI inflows increasing exchange rate volatility. As revealed by the study, this relationship is however weak for South Africa. The possible reason adduced by the study is the sound capital flow management policy of the South African Reserve Bank.

Further attempts were made by Aliyu (2009) and employed standard deviation measure of exchange rate volatility based quarterly observation and further assesses the impact of exchange rate volatility on non-oil export flows in Nigeria between 1986 and 2006. Empirical result revealed that exchange rate volatility decreased non-oil exports in Nigeria.

In another study, Aliyu (2009) examined the impact of oil price shock and exchange rate volatility on economic growth in Nigeria and measuring exchange rate volatility as the consumer price index based real exchange rate approach. But he failed to examine the degree and persistency of exchange rate volatility using standardized econometric. However, among the entire studies on the macroeconomic effects of exchange rate volatility in Nigeria over the past three decades, it is only the study of Olowe (2009) that is found to investigate the volatility of Naira/Dollar exchange rates in Nigeria using several variants of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. He used monthly data over the period January 1970 to December 2007 and found that all the GARCH family models indicated that volatility is persistent and reported similar evidence for the fixed exchange rate and managed float rate regimes.

This study employs the use of ARIMA models to obtain the best model for predicting the Dollar-Naira exchange rate, and specifically employed the *auto.arima* function in R in order to determine the optimal model without going through the conventional process. The data analysed in this paper are the annual time series data on Dollar-Naira exchange rate for a period of 46 years (1972 - 2017) from the Bulletin of Central Bank of Nigeria (CBN) and *R* version 3.2.5 was used for the analysis.

II. Materials and Methods

A. Tests for stationarity

There are several tests of stationarity but this paper will discuss four major tests: Graphical analysis, the Autocorrelation function and Partial autocorrelation function, and Unit root test using Dickey-Fuller test

The autocorrelation function as a lag k denoted by ρ_k is defined as

$$\rho = \frac{\gamma_k}{\gamma_0} = \frac{\text{covariance at lag k}}{\text{variance}} \qquad (1)$$

where covariance at lag k and variance are as follows:

$$\gamma_k = \frac{\sum (Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{N}$$

$$\gamma_0 = \frac{\sum (Y_t - \bar{Y})}{N}$$

where N is the sample size and $\bar{Y}$ is the sample mean. Therefore, the sample autocorrelation function at lag k is

$$\hat{p}_k = \frac{\gamma_k}{\gamma_0}$$

which is simply the ration of sample covariance (at lag k) to sample variance. If the function $\hat{P}_k$ is well-defined, its value must lie between -1 and 1. The *Partial Autocorrelation Function (PACF)* is used to measure the correlation between an observation *k* period ago and the current observation, after controlling for observations at intermediate lags (i.e. at lags <*k*) . At lag 1, PACF (1) is same as ACF (1).

Normally, the stochastic process governing a time series is unknown and so it is not possible to determine the actual or theoretical ACF and PACF values. Rather these values are to be estimated from the training data, i.e. the known time series at hand. The estimated ACF and PACF values from the training data are respectively termed as sample ACF and PACF. The plot of ACF and PACF are terms correlogram.

A test of stationary that has become extensively admired over the past several years is the unit root test Unitroot test (Dickey Fuller) Considering the unit root,

$$y_t = \rho y_{t-1} + u_t \qquad (2)$$

where "e" is a white-noise error term. As if p = 1, which is in the unit root, the above turn into: $y_t = y_{t-1} + e_t$ i.e. a random walk model exclusive of drift, which is well-known as a non-stationarystochastic process. Thus, if the estimates p is statistically equal to one, then y_t is nonstationary. Mostly time series data have problem of unit root, so application of unit root test is valuable in time series data related studies .The above can be done by Ordinary Least Square method by manipulating the above equation as to obtain

$$y_t - y_{t-1} = \rho y_{t-1} - \; y_{t-1} + u_t$$

$= (\rho - 1)y_{t-1} + u_t$ ……………………………………..(3)

This can be alternatively written as:

$\Delta y_t = \delta y_{t-1} + u_t$ ……………………………………..(4)

B. Time series models

There are several models in time series analysis and they are as follows:

i.) Autoregressive (AR) process

The equation below is an example of an Autoregressive process

$(Y_t - \delta\ ) = \alpha_1\,(Y_{t-1} - \delta) - +u_t$ ………………(5)

where δ is the mean of *Y* and where u_t is an uncorrelated random error term with zero mean and constant variance σ^2 (i.e., it is *white noise*), then we say that Y_t follows a first-order autoregressive, or AR (1),stochastic process. Here the value of *Y* at time *t* depends on its value in the previous time period and a random term; the *Y* values are expressed as deviations from their mean value. In other words, this model says that the forecast value of *Y* at time *t* is simply some proportion (=α_1) of its value at time $(t - 1)$ plus a random shock or disturbance at time *t*; again the *Y* values are expressed around their mean values. But if we consider this model,

$$(y_t - \delta) = \alpha_1(Y_{t-1} - \delta) + \alpha_2(Y_{t-2} - \delta) + u_t \qquad (6)$$

then we say that Y_t follows a second-order autoregressive, or AR (2)process. That is, the value of *Y* at time *t* depends on its value in the previous two time periods, the *Y* values being expressed around their mean value δ. In general, we can have

$$(y_t - \delta) = \alpha_1(Y_{t-1} - \delta) + \alpha_2(Y_{t-2} - \delta) + \ldots + \alpha_p(Y_{t-p} - \delta) + u_t \qquad (7)$$

in which case Y_t is a pth-order autoregressive, or AR(p),process.

ii.) Moving Average (MA) process

The AR process just discussed is not the only mechanism that may have generated *Y*. Suppose we model *Y* as follows:

$$Y_t = u + \beta_0 u_t + \beta_1 u_{t-1} \qquad (8)$$

where μ is a constant and *u* is the white noise stochastic error term. Here *Y* at time *t* is equal to a constant plus a moving average of the current and past error terms. Thus, we say that *Y* follows a first-order moving average or an MA (1), process. But if *Y* follows the expression

$$Y_t = u + \beta_0 u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} \qquad (9)$$

then it is an MA (2) process.

More generally,

$$Y_t = u + \beta_0 u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \ldots + \beta_p u_{t-p} \qquad (10)$$

iii.) The Autoregressive Moving Average (ARMA) models

An ARMA (*p, q*) model is a combination of AR (*p*) and MA (*q*) models and is suitable for Univariate time series modeling. In an AR (*p*) model the future value of a variable is assumed to be a linear combination of *p* past observations and a random error together with a constant term. Mathematically the AR (*p*) model can be expressed as;

$$\mu + \sum \phi_i Y_{t-1} + \in_t = C + \phi_1 Y_{t-1} + \phi_2 Y_{t-2}$$
$$\ldots.. + \phi_p Y_{t-p} + \in_t \qquad (11)$$

Here Y_t and ε_t are respectively the actual value and random error (or random shock) at timeperiod *t, (i* = 1, 2... *p*), ϕ = are model parameters and *c* is a constant. The integer constant *p* is known as the order of the model. Sometimes the constant term is omitted for simplicity. Usually For estimating parameters of an AR process using the given time series, the Yule-Walker equations are used.Just as an AR (*p*) model regress against past values of the series, an MA (*q*) model uses past errors as the explanatory variables. The MA (*q*) model is given by

$$\sum \phi_j \varepsilon_{t-1} + \varepsilon_t = \mu + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2}$$
$$\ldots.. + \phi_q Y_{t-q} + \varepsilon_t \qquad (12)$$

Here μ is the mean of the series, (j =1, 2... *q*) θ_J= are the model parameters and *q* is the Order of the model. The random shocks are assumed to be a white noise process, i.e. a sequence of independent and identically distributed (i.i.d) random variables with zero mean and a constant variance σ. Generally, the random shocks are assumed to follow the typical normal distribution. Mathematically an ARMA (*p, q*) model is represented as

$$Y_t = C + \in_t + \sum \varphi Y_{t-1} + \sum \theta_j \in_t \qquad (13)$$

Here the model orders *p*, *q* refers to *p* autoregressive and *q* moving average terms.

iv.) Autoregressive Integrated Moving Average (ARIMA) model

The ARMA models, described above can only be used for stationary time series data. However in practice many time series such as those related to socio-economic and business show non-stationary behaviour. Time series, which contain trend and seasonal patterns, are also non-stationary in nature. Thus from application view point ARMA models are inadequate to properly describe non-stationary time series, which are frequently encountered in practice. For this reason the ARIMA model is proposed, which is a generalization of an ARMA model to include the case of non-stationarity as well. In ARIMA models a non-stationary time series is made stationary by applying finite differencing of the data points. This is written as ARIMA (p, d, q).

Here, *p*, *d* and *q* are integers greater than or equal to zero and refer to the order of the Autoregressive, integrated, and moving average parts of the model respectively. The integer *d* controls the level of differencing. Generally *d*=1 is enough in most cases. When *d*=0, then it reduces to an ARMA (*p, q*) model. It is widely used for non-stationary data, like economic and stock price series.

C. Box-Jenkins Methodology

After describing various time series models, the next issue to our concern is how to select an appropriate model that can produce accurate forecast based on a description of historical pattern in the data and how to determine the optimal model orders. Box and Jenkins (1973) developed a practical approach to build ARIMA model, which best fit to a given time series and also satisfy the parsimony principle. Their concept has fundamental importance on the area of time series analysis and forecasting.

The Box-Jenkins methodology does not assume any particular pattern in the historical data of the series to be forecasted. Rather, it uses a three step iterative approach of ***model identification, parameter estimation,*** and ***diagnostic checking*** to determine the best parsimonious model from a general class of ARIMA models. This three-step process is repeated several times until a satisfactory model is finally selected. Then this model can be used for forecasting future values of the time series.

The **`auto.arima`** *function*

This is a function in the package *forecast* in *R*. It returns the best ARIMA model according to either of the information criteria: AIC, AICc or BIC value. The function conducts a search over possible models within the order constraints provided.

D. ***Hyndman-Khandakar (2008) algorithm for automatic ARIMA modelling***

1. The number of differences d is determined using repeated KPSS tests.
2. The values of p and q are then chosen by minimizing the AICc after differencing the data d times. Rather than considering every possible combination of p and q, the algorithm uses a stepwise search to traverse the model space.
(a) The best model (with smallest AICc) is selected from the following:
ARIMA(2,d,2), ARIMA(0,d,0), ARIMA(1,d,0), ARIMA(0,d,1).
If d = 0 then the constant c is included; if d ≥ 1 then the constant c is set to zero. This is called the ”current model”.

(b) Variations on the current model are considered: vary p and/or q from the current model by ±1; include/exclude c from the current model. The best model considered so far (either the current model, or one of these variations) becomes the new current model.
(c) 2(b) is repeated until no lower AICc can be found.

III. Analysis

Table 1: Exchange rate of Dollar-Naira from 1972 – 2017

Year	Exchange rate (₦)	Year	Exchange rate (₦)
1972	**0.66**	1995	**21.90**
1973	**0.66**	1996	**21.88**
1974	**0.63**	1997	**21.89**
1975	**0.62**	1998	**21.89**
1976	**0.62**	1999	**92.34**
1977	**0.65**	2000	**101.70**
1978	**0.61**	2001	**111.23**
1979	**0.60**	2002	**120.58**
1980	**0.55**	2003	**129.22**
1981	**0.62**	2004	**132.89**
1982	**0.67**	2005	**131.27**
1983	**0.72**	2006	**128.65**
1984	**0.77**	2007	**125.81**
1985	**0.89**	2008	**118.55**
1986	**1.75**	2009	**148.90**
1987	**4.02**	2010	**150.30**
1988	**4.54**	2011	**153.86**
1989	**7.36**	2012	**157.50**
1990	**8.04**	2013	**157.31**
1991	**9.91**	2014	**183.51**
1992	**17.30**	2015	**204.85**
1993	**22.07**	2016	**345.85**
1994	**22**		

Source: CBN bulletin, 2015

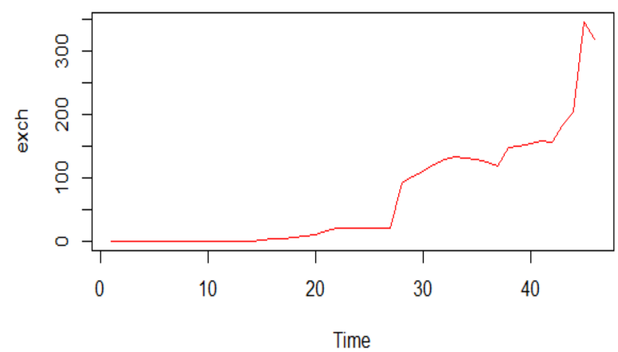

Fig. 1: Time plot of Dollar – Naira from 1972-2017

The time plot shows that the time series data is not stationary since the time plot show upward movement (trend) which means that the mean of Exchange rate in Nigeria is changing and there is no stability in the variance of the time series data.

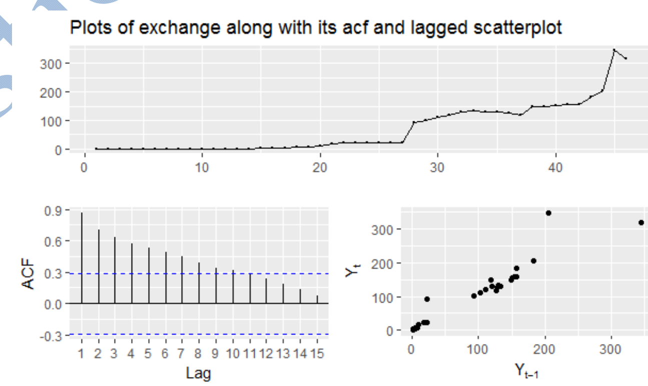

Fig. 2: Plots of Exchange rates series before differencing

There is evidence of non stationarity in the above ACF plot, the relationship between the series and the lagged is also obvious, and moreover since the variances are not also constant, Dickey-Fuller test cannot be used. The next step is to difference or transform the data.

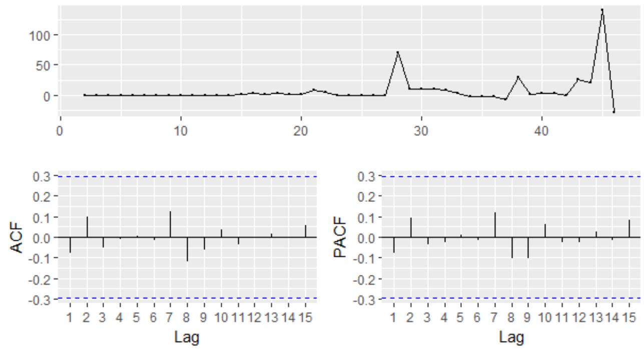

Fig. 3: ACF and PACF of series after differencing

With no spike outside bands in the ACF and PACF plots, it can be assumed that the series is stationary at order 1.

Table 2: ARIMA Model Identification

Model	Log-Likelihood	AIC	BIC
ARIMA (0,1,0)	-208.81	419.62	421.42
ARIMA (1,1,0)	-208.80	421.61	425.22
ARIMA (2,1,0)	-207.17	420.34	425.76
ARIMA (0,1,1)	-208.80	421.61	425.22
ARIMA (2,1,1)	-207.17	422.34	429.57
ARIMA (1,1,2)	-207.30	422.59	429.82
ARIMA (1,1,3)	-207.30	424.59	433.62
auto.arima	**-206.96**	**417.92**	**421.53**

From table above, it can be observed that the optimal model is ARIMA (0, 1, 0) that is based on the selection criterion log-likelihood, AIC, and BIC. This gives the best fit for the data.

The model is now

```
ARIMA(0,1,0) with drift
Coefficients:
drift
      7.0409
s.e.  3.5851
sigma^2 estimated as 591.5: log likelihood=-206.96
AIC=417.92   AICc=418.2   BIC=421.53
```

A. *Testing for residual white noise in the optimal model*

One of the commonest tests for model adequacy is making sure that the residual of the optimal model must be white noise by the ACF for residuals and by the use of theBox-Ljung test.

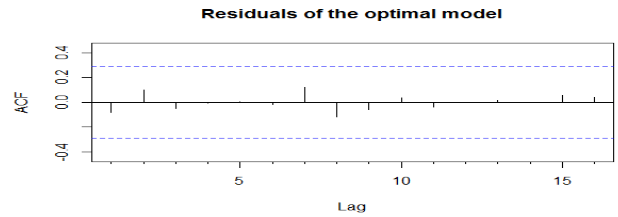

Fig. 4: The ACF plot of the residuals from the ARIMA (0,1,0) model

B. *Box-Ljung test*

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X-squared = 13.553, df = 20,
p-value = 0.8524
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The ACF plot of the residuals from the ARIMA (0,1,0) model shows all correlations within the threshold limits indicating that the residuals are behaving like white noise. A Box-Ljung test returns a large p-value (0.8524), also suggesting the residuals are white noise and that the model is adequate

Table 3: Summary measures of the Forecast Accuracy

Model	ME	RMSE	MPE
ARIMA (0,1,0)	6.7707	24.78	421.42
ARIMA (1,1,0)	5.1910	23.76	425.22
ARIMA (2,1,0)	6.7978	24.78	425.76
ARIMA (0,1,1)	5.2356	23.75	425.22
ARIMA (2,1,1)	5.5258	23.83	429.57
ARIMA (1,1,2)	6.8878	24.78	429.82
ARIMA (1,1,3)	5.5299	23.82	433.62
auto.arima	**0.0014**	23.78	**-324.09**

where ME, RMSE, and MPE stand for, Mean Error, Root Mean Square Error, and Mean Percentage Error. The lowest values of the measures of accuracy indicate the optimal ARIMA model for reliable forecast.

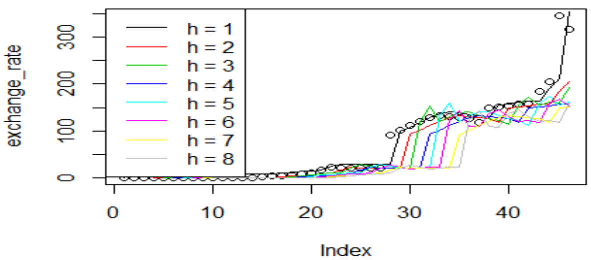

Fig. 5: Comparison of various ARIMA models

In fig. 5, 1 represents the first model, 2 the second, 3 the third and so on. It can be seen from the chart that the best ofthemodels is the first, it fits the real series more than the others

Table 3: Forecasts of Exchange rate for 13 years (2018 - 2030)

Year	Forecasts (₦)	Lo.95 (₦)	Hi.95 (₦)
2018	324.54	276.87	372.21
2019	331.58	264.17	399.00
2020	338.62	256.06	421.19
2021	345.66	250.33	441.00
2022	352.70	246.11	459.30
2023	359.75	242.98	476.51
2024	366.79	240.67	492.91
2025	373.83	239.00	508.66
2026	380.87	237.86	523.88
2027	387.91	237.17	538.65
2028	394.95	236.85	553.05
2029	401.99	236.86	567.12
2030	409.03	237.16	580.91

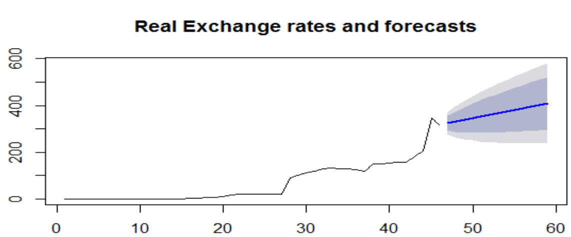

Fig. 6: Forecasts made using the optimal model (in blue)

The table and the figure (table 3 and figure 6) above show upward movement in the forecasts of Dollar to Naira from 2018 – 2030. Using the model obtained, this means there will be a continuous and perpetual increase in the exchange rate unless a measure is taken by the appropriate authority.

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IV. Results

Result of the analysis revealed that the series became stationary at first difference. The diagnostic checking has shown that ARIMA (0, 1, 0) is appropriate or optimal model based on the Log-likelihood, AIC, and BIC. The performance of *auto.arima* function in R gives the best model for exchange of dollar to Naira without the rigours of testing for other ARIMA models. With Minimum Mean Error (ME), Mean Percentage Error (MPE), and Root Mean Squared Error (RMSE), which proves that ARIMA (0, 1, 0) model is the best or optimal model. The residual of the forecast model is white noise, and the hypothesis of adequate model using B-J test is not rejected, which means that the model is adequate. The model is used to make some forecasts (2018 - 2030). Also other models were compared graphically with the optimal models.

V. Conclusion

Using the results above, it can be concluded that the best model for forecasting Dollar to Naira exchange rate is ARIMA (0,1,0) obtained through the use of the function *auto.arima*. Time series data analysts are encouraged to explore R in order to discover better methods.

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