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Evaluation of Models for Forecasting Daily Foreign Exchange Rates Between Nigerian Naira and US Dollar Amidst Volatility

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Abstract

In her quest to put the nations' foreign exchange policy in line with global practice, the Central Bank of Nigeria (CBN) in the mid of 2016 made a paradigm shift by unveiling flexible foreign exchange policy driven purely by market forces. Consequently, forecasting models reported during pegging policy era may be deeming obsolete. This paper proposed a prediction model for future daily selling exchange rate between Nigerian Naira and United States Dollar in the interbank market amidst volatility using daily rates made available by the Central Bank of Nigeria over the periods July, 2016 to October, 2017. We applied the Box-Jenkins methodology to the Naira – US Dollar exchange rate series in order to build an adequate and well specified prediction model. On the first phase of the study, we checked the stationarity of the series and based on Augmented Dickey-Fuller test and correlogram, the series is stationary at level. The findings revealed that the future daily exchange rate of Naira per US Dollar depends on its past rates and associated innovations. This is evident from the fact that $\mathrm{ARMA}(2,3)$ turned out parsimonious model for forecasting the parity between the two currencies on the basis of Bayesian Information Criterion. The said model yielded error of forecast (MAPE) within ten percent.

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1. Introduction

The central bank of Nigeria in the mid of 2016 in a change of tack allow the Naira to float after declining growth consecutively seen for two quarters. This change of tack put Nigeria in line with most central banks, including the Bank of England and the Naira likely to plunge when the system starts (Laessing & Brock, 2016). In line with this speculation, the parity between the Nigerian Naira (NGN) and the United States Dollar (USD) now stood at 300-odd Naira opposed to N197 per US Dollar in the interbank market amounting to the view that in the modern world, exchange rates of the most successful countries are tends to be floating (Sullivan, 2001). This volatility has received attention of many researchers in the recent times as (Brownlees, Engle, & Kelly, 2011) reported that volatility modeling has been one of the most active financial time series research areas in the past decade. Given the uncertainty and risk associated with volatile exchange rates as well as the frequent exchange rate policy changes in many developing countries, there is need to measure exchange rate volatility across time (Emenike, 2016). Foreign Exchange (Forex) is a type of transaction where a party obtains some units in one currency to buy proportion amount in another currency (Sidehabi, et al, 2016). This exchange is usually conducted in pair currency. The most popular pair and trade worldwide is Euro vs. USD (EUR / USD). In Nigeria, the most popular pair and trade is Naira – United States Dollar, because according to (Central Bank of Nigeria, 2016), the dollar is the intervention currency in the market; while the exchange rates of other currencies are based on cross reference to the naira - dollar exchange rates.

Forecasting models reported during pegging policy era may be deeming obsolete with the unveiling of this flexible foreign exchange policy driven purely by market forces, since the parity is no longer pegged. Hence, this paper aimed to propose a basic framework for forecasting and understanding the future daily exchange rate dynamics between Nigerian Naira and United States Dollar in the interbank market amidst volatility.

2. Review of Literature

In the past decades, many researchers take the modeling approach to describe financial data (Jianan Han & Fang Wang, 2016). In light of this, one may not be wrong to argue that handful of literature on prediction modeling of exchange rates based on Autoregressive Integrated Moving Average (ARIMA) models are readily available. This claim is visible in the work of (Tlegenova, 2015), who opined that there are lots of works done on time series based on prediction modeling of foreign currency rates in literature and many authors created and tested the ARIMA model to forecast exchange rates. He further outline that the Autoregressive Integrated Moving Average model is comparatively accurate model to forecast exchange rates while studying the exchange rate forecasting of USD, Euro and Singapore dollar with respect to the Kazakh tenge. In view of (Akincilar, et al, 2011), exchange rates forecasting is an extensively discussed issue in the literature. Moreover, he reported that mid and long term forecasts can be done more accurately and reliably by ARIMA models among other forecasting methods (MA, Holt's method, and Winter's method) while studying the exchange rate forecasting of United States (US) Dollar, Euro and Great Britain Pound against the Turkish Lira. This opinion is in line with the words of (Abdullah, 2012) who noted that one of widely used time series models is ARIMA. Furthermore, (Abdalla, 2012) examined the daily returns of exchange rate series of nineteen Arab countries for the period ranging from January 1, 2000 to November 19, 2011. The currencies considered are the United Arab Emirates dirham, Bahraini Dinar, Djiboutian Franc, Algerian Dinar, Egyptian pound, Iraqi Dinar, Kuwaiti Dinar, Lebanese Pound, Libyan Dinar, Moroccan Dirham, Mauritanian Ouguiya, Omani Rial, Qatari Riyal, Saudi Arabian Riyal, Somali Shilling, Syrian Pound, Tunisian Dinar and Yemeni Rial, all against the US Dollar as cited by (Emenike, 2016). Additionally, in their paper titled "Forecasting Exchange rate between the Ghana Cedi and the US dollar using time series analysis" (Appiah & Adetunde, 2011) discovered that ARIMA (1, 1, 1) was the best model for Ghana's cedi against US dollar and a forecast for two years were made from January 2011 to December 2012. Their findings also revealed that predicted rates were consistent with the depreciating trend of the series. Nevertheless, the literature on Naira – US Dollar exchange rates prediction modeling could not be exceptional from the claim: there are lots of works done on time series based on prediction modeling of foreign currency rates in literature as noted earlier. This is defensible as number of researchers have reported different models for predicting exchange rates between Naira and US Dollar. On a similar note, (Nwankwo, 2014) discovered that residuals is negligible when ARIMA (1 0 0) identified as the model that best fit the average yearly exchange rates for US Dollar in Naira for the period 1992 to 2011. Likewise, (Onasanya & Adeniji, 2013) found that for the period January 1994 to December 2011, ARIMA (1, 2, 1) is the best model that explains the NGN/USD exchange rates. The results of their findings further uncovered that the error is white noise and presence of no serial correlation, thus confirming the suitability of the model for forecasting. In a related work, a comparison of Central Bank of Nigeria exchange rates, Bureau de Change rates and Inter-bank exchange rates over a period of thirty-five years by (Mojekwu, et al, 2011) reveals that there are variations in modes of monetary exchange rates against US Dollars in Nigeria. The study uses Autoregressive integrated moving average model to fit time series to the three sets of data.

With the unveiling of the flexible foreign exchange policy driven purely by market forces by the Central Bank of Nigeria in the mid of 2016 and the consequent volatility in the nation's Forex market, forecasting models reported by number of authors like (Emenike, 2016) (Nwankwo, 2014) and (Onasanya & Adeniji, 2013) among others during pegging policy era may be deeming obsolete since the parity is no longer pegged. Hence the need for a basic framework for forecasting and understanding the future daily exchange rate dynamics between Nigerian Naira and United States Dollar amidst volatility.

3. Objectives

The general objective of the paper is to propose a prediction model for future daily exchange rates between Naira and US Dollar. The specific objectives are to:

a) select a parsimonious model for predicting daily parity between Naira and US Dollar.
b) determine the adequacy of the selected model based on model diagnostics tools.
c) evaluate the effectiveness of the model considered on the basis of performance metrics

4. Methodology

In order to achieve the aim of this study, we adopt the notion introduced by Box and Jenkins (1976). The notion is also known as $ARIMA\ (p, d, q)$, specifically, the three parameters in the model are: the autoregressive parameter (p), the number of differencing passes (d), and moving average parameter (q) (Indrabayu, et al, 2013). ARIMA is used to predict a value in a response time series as a linear combination of its own past values and past innovations. The general form of the ARIMA model of order p, d and q is presented as follows:

$$\Delta^d\, Y_t \left(1 - \omega_1 L - \omega_2 L^2 - \ldots - \omega_p L^p\right) = \varepsilon_t (1 + \tau_1 L + \tau_2 L^2 + \ldots + \tau_q L^q) \qquad (1)$$

In compact notation, the equation can be rewritten as:

$$\Delta^d \Omega(L) Y_t = T(L)\varepsilon_t$$

Where $\Delta = 1 - L$ (difference operator)
$d =$ Difference dimension
$Y_t =$ Response variable at time t
$\mathcal{E}_t =$ Innovation term at time t
$L =$ Lag operator; generally $L^n Y_t = Y_{t-n}$ while,
$\Omega(L) and\ T(L) =$ Are respectively p and q-order polynomials in the lag operator.
The Naira-US Dollar ARIMA modeling methodology is categorically divided into three, as (Abdullah, 2012) reported that ARIMA model for any variable involves primarily three steps: identification, estimation and diagnostic checking. Thus, these three steps are now explained for the Nigerian Naira – United States Dollar Selling Exchange Rates forecasting model.

4.1. Model Identification

The first phase of ARIMA modelling is the identification of the number of differencing passes (d) and the proper orders of AR and MA parameters (p and q respectively) for the model. However, this can only be achieved if the series is stationary, stationarity can be assessed by either Augmented Dickey – Fuller (ADF) test, runs sequence plot or correlogram.

4.1.1 Stationarity. In order to build an adequate and well specified Naira – US Dollar exchange rates forecasting model, we subjected the series to stationarity test using Augmented Dickey – Fuller (ADF) Test along with runs sequence plot and correlogram. The ADF test the existence of unit root in the exchange rate series and it is also important in determining whether the model to be identified contains constant term. Computational formula of Dickey – Fuller Test is as follows:

$$DF_T = \frac{\hat{\gamma}}{SE(\hat{\gamma})} \quad \text{(a)}$$

The testing procedure for the ADF test is the same as for the Dickey–Fuller test but it is applied to the model:

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} + \Delta y_{t-p+1} + \varepsilon_t \quad \text{(b)}$$

The unit root test is then carried out under the null hypothesis $\hat{\gamma} = 0$ against the alternative hypothesis of $\hat{\gamma} < 0$. Once a value for the test statistics computed, it can be compared to the relevant critical value for the Dickey–Fuller Test.
Where $\hat{\gamma}_k =$ Estimated autocorrelation of the series at lag k.
The statement of the hypotheses is as follows:
H_0: The Naira – US Dollar Exchange Rate series have unit root.
H_1: The Naira – US Dollar Exchange Rate series does not have unit root.
While the mathematical form of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are respectively given in (c) and (d):

$$\gamma_k = \frac{\frac{\sum(Y_t - \bar{Y})\sum(Y_{t+k} - \bar{Y})}{n}}{\frac{\sum(Y_t - \bar{Y})}{n}} \quad \text{(c)}$$

$$\phi_{p+1,j} = \phi_{p,j} - \phi_{p+1,p+1}\phi_{p,p-j+} \quad \text{(d)}$$

Where: $\phi_{p+1,p+1} = \frac{\gamma_{p+1} - \sum \phi_{p,j}\gamma_{p+1-j}}{1 - \sum \phi_{p,j}\gamma_j}$

From the summary of the Augmented Dickey- Fuller Test (Table 1), it is apparent that the Naira – US Dollar exchange rates series is stationary at level, first difference (1st Diff) and second difference (2nd Diff) as it can be seen that ADF Statistics are less than the test critical values at the significance levels of 1%, 5% and 10% with exceptional case at level without intercept and trend, meaning that the process is not a random walk.

Table 1. ADF unit root test summary at different form

ADF TEST			Test equation Parameters		
			Intercept	Intercept & Trend	None
At Level	T-statistic		-8.7254	-8.6841	0.8971
	Test Critical values	1%	-3.4507	-2.5722	-2.5722
		5%	-2.8704	-1.9418	-1.9418
		10%	-2.5715	-1.6160	-1.6160
1st Diff	T-statistic		-8.8609	-9.0527	-8.8087
	Test Critical values	1%	-3.4506	-3.9870	-2.5722
		5%	-2.8703	-3.4239	-1.9418
		10%	-2.5715	-3.1349	-1.6160
2nd Diff	T-statistic		-9.8179	-10.1467	-9.7291
	Test Critical values	1%	-3.4516	-3.9883	-2.5725
		5%	-2.8708	-3.4246	-1.9419
		10%	-2.5718	-3.1354	-1.6160

The result of the ADF test is further consolidated by the runs sequence plot (Figure 1) and correlogram of the series (Figure 2). It is obvious that the pattern of the runs sequence plot contains neither time variant trend nor seasonal cycles and both Autocorrelation (AC) Function and Partial Autocorrelation (PAC) Function plots rapidly decayed to zero as depicted by Figure 1 and 2 respectively. Additionally, it could be deduced from the appearance of the AC and PAC Function plots that mixed model is likely to best fit the series.

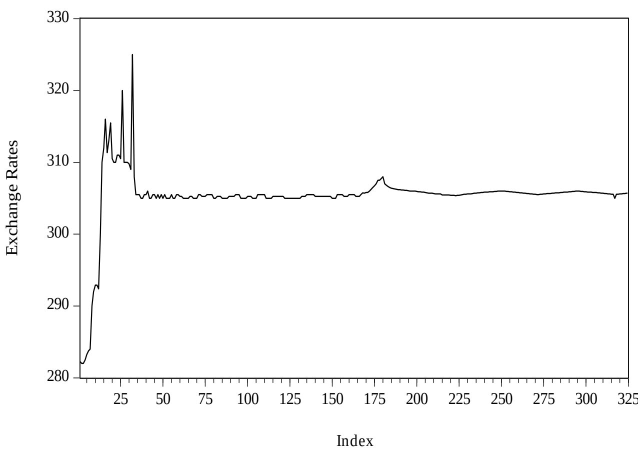

Figure 1. Runs sequence plot of naira-us dollar exchange rates

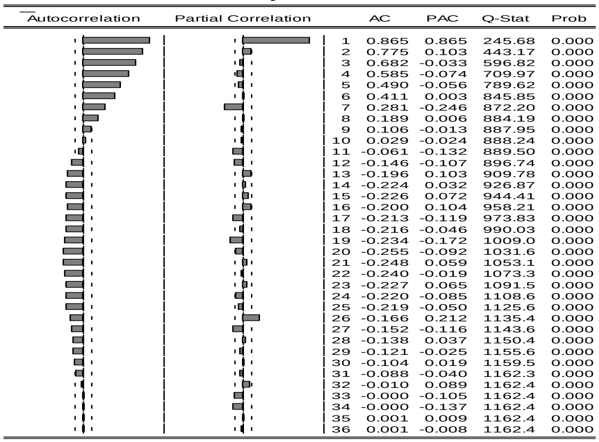

Figure 2: correlogram of the naira –us dollar exchange rate

The Naira – US Dollar series can be best fit by ARIMA $(p, 0, q)$ equivalently written as ARMA $(p,\ q)$ since the process is stationary at level and both AC and PAC Function plots rapidly decayed to zero, hence the next step is to find a parsimonious ARIMA $(p, 0, q)$ model. This step is not without some difficulties and involves a lot of subjectivity (Nasiru & Olanrewaju, 2015). However, it is possible to overcome the difficulties by subjecting the choice of the orders of the components on the basis of information criterion. The parsimonious model is one with the smallest Akaike information criterion (AIC) or Schwarz Bayesian criterion (SBC) values. Of the two criteria, the SBC is preferable (Dimitrios & Stephen, 2011). Therefore, the identification of the orders of the ARIMA components for the Naira-US Dollar exchange rates series is based on SBC (also known as Bayesian Information Criterion) and Table 2 shows the number of ARIMA models estimated alongside their respective Bayesian Information Criterion (BIC) in ascending order of magnitude. The parsimonious model is $ARMA\ (2,\ 3)$ since it exhibited less BIC value of 3.977915 as shown in Table 2. Visual views of the BIC values and forecasted rates of the 25 models are presented in Figure 3 and Figure 4 respectively using simple Bar Chart and runs sequence plot to further highlight the selection justification of the orders of the Autoregressive (AR) and the Moving Average (MA) models.

Table 2. ARMA information criterion values

Model	LogL	AIC	BIC*	HQ
(2,3)	-626.167859	3.896418	3.977915	3.928943
(3,3)	-625.761092	3.900068	3.993209	3.937241
(2,4)	-625.866802	3.900719	3.993859	3.937891
(3,4)	-624.178152	3.896481	4.001264	3.938300
(1,1)	-638.972056	3.956751	4.003321	3.975337
(2,0)	-638.979882	3.956799	4.003369	3.975385
(3,2)	-631.625076	3.930000	4.011498	3.962526
(3,0)	-638.671133	3.961053	4.019266	3.984286
(1,2)	-638.675102	3.961078	4.019290	3.984310
(2,1)	-638.766174	3.961638	4.019851	3.984871
(4,2)	-631.261517	3.933917	4.027057	3.971089
(2,2)	-637.780352	3.961725	4.031580	3.989605
(4,3)	-629.437472	3.928846	4.033629	3.970665
(4,0)	-638.349625	3.965228	4.035084	3.993108
(1,3)	-638.395613	3.965511	4.035367	3.993391
(3,1)	-638.588780	3.966700	4.036555	3.994580
(1,0)	-647.560688	4.003450	4.038378	4.017390
(4,1)	-637.188094	3.964234	4.045732	3.996760
(4,4)	-628.737083	3.930690	4.047115	3.977155
(1,4)	-638.315526	3.971172	4.052670	4.003698
(0,4)	-682.099981	4.234461	4.304317	4.262341
(0,3)	-703.902005	4.362474	4.420687	4.385707
(0,2)	-750.606337	4.643731	4.690301	4.662318
(0,1)	-810.628941	5.006947	5.041875	5.020887
(0,0)	-929.272910	5.730910	5.754195	5.740203

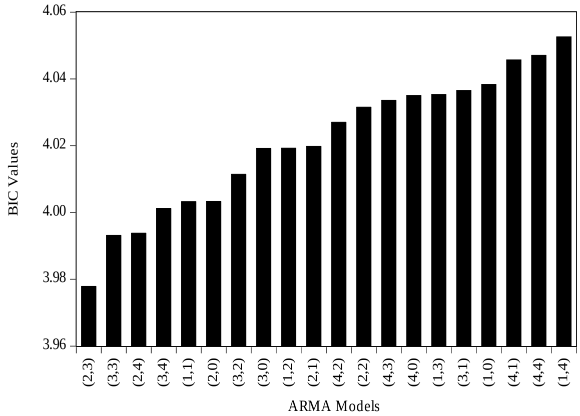

Figure 3. Simple bar of BIC values

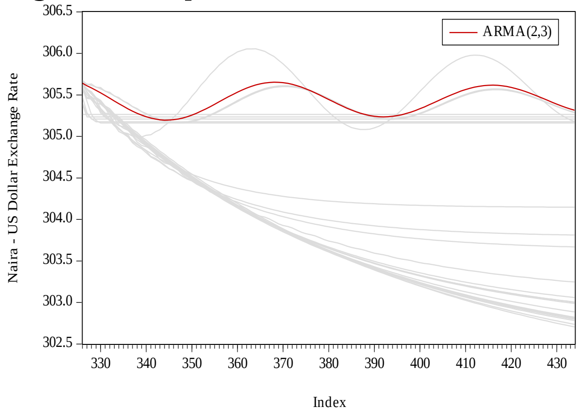

Figure 4. Runs sequence plot of forecasted naira – US dollar exchange rate

Therefore, the mathematical structure of the proposed model [i.e. $ARMA\ (2,3)$] is as follows:

$$y_t = \omega_o + \omega_1 y_{t-1} + \omega_2 y_{t-2} + \varepsilon_t - \tau_1\varepsilon_{t-1} - \tau_2\varepsilon_{t-2} - \tau_3\varepsilon_{t-3} \quad (2),$$

since the process is stationary at level and the Naira-US Dollar Exchange rates revolve around a constant (ω_o) value as noticeable in Figure 1. However, the constant term ω_o in a non-seasonal ARIMA process is related to the mean μ of the process and the AR coefficients (Pankratz, 2009). This expression can be put in mathematical form as follows:

$$\omega_o = \hat{\mu}\left(1 - \sum_{i=1}^{p} \widehat{\omega}_i\right) \quad (3)$$

4.2. Model Estimation

Having identified the orders of the component parameters, that is $p = 2,\ d = 0\ and\ q = 3$, next is to estimate the AR and MA coefficients of the model given in equation (2). The estimation of the AR model parameters can be done by the Yule-walker method. While the estimation of the MA model parameters can be done by the notion of casual representation. But these coefficients can be easily estimated with aid of application software like Eviews 9.5 and Table 3 displays the estimated values of the coefficients of ARIMA (2, 0, 3).

Table 3. Estimated coefficients and significant test of ARIMA (2, 0, 3)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	305.4345	0.812067	376.1198	0.0000
AR(1)	1.975099	0.002753	717.3858	0.0000
AR(2)	-0.992440	0.002495	-397.7488	0.0000
MA(1)	-1.332040	0.019661	-67.74903	0.0000
MA(2)	0.308788	0.029897	10.32827	0.0000
MA(3)	0.082470	0.024607	3.351479	0.0009

Thus, by using the relation in (3) and substituting the values of the coefficients from the Table 3 into equation (2):

$$y_t = 5.2840 + 1.9751y_{t-1} - 0.9924y_{t-2} + \varepsilon_t - 1.3320\varepsilon_{t-1} + 0.3088\varepsilon_{t-2} + 0.0825\varepsilon_{t-3} \quad (4)$$

Furthermore, it can be clearly seen from Table 3 that the coefficients are all significant as the p-values are less than α = 0.05 and confidence intervals at 90%, 95% and 99% is also presented in Table 4.

Table 4. Confidence intervals of coefficients of ARIMA (2, 0, 3)

Variable	Coefficient	95% CI Low	95% CI High	99% CI Low	99% CI High
C	305.4345	303.8367	307.0322	303.3301	307.5388
AR(1)	1.975099	1.969682	1.980515	1.967964	1.982233
AR(2)	-0.992440	-0.997349	-0.987531	-0.998905	-0.985974
MA(1)	-1.332040	-1.370723	-1.293357	-1.382990	-1.281090
MA(2)	0.308788	0.249966	0.367609	0.231312	0.386263
MA(3)	0.082470	0.034057	0.130883	0.018704	0.146236

4.3. Diagnostic Checking

This is an examination of the goodness of fit of the selected model and it is usually on the basis of the residual analysis. The common diagnostic tools among others are Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF) and Ljung-Box Q- Statistics (Q-Stat) of the residuals. The Ljung-Box Q- Statistics is considered as an overall check of goodness of fit of a model by testing presence of serial correlation in the residuals. For a given series y of length n, (NIST/SEMATECH, 2013) noted that the test statistic is defined as:

$$Q_m = n(n+2)\sum_{k=1}^{m}\frac{\hat{\gamma}_k^2}{n-k} \sim \chi^2_{1-\alpha,\ h} \quad (5)$$

Where $\hat{\gamma}_k$ = Estimated autocorrelation of the series at lag k

n = Sample size (the number of residuals)

m = Number of lags being tested

h = Degrees of freedom $(h = m - p - q)$

p and q = Number of parameters from the $ARMA\ (p, q)$ model fit to the data

This statistic will subject the residuals to the fulfilment of the models assumption of being independent and normally distributed based on the following hypotheses:

H_0: Residuals are random (white noise)

H_1: Residuals are non-random (not white noise)

Decision: If the Q_m value is less than critical value of χ^2 at specified significance level, do not reject the null hypotheses (H_o)
Table 5 presents the ACF, PACF and Q – Statistics at various lags and it can be observed that the values of the both ACF and the PACF revolve around zero meaning that the residuals are independent.

Table 5. AC and PAC functions of residuals and Q – statistics

Lag	AC	PAC	Q-Stat	Prob.	Lag	AC	PAC	Q-Stat	Prob.
1	-0.013	0.0515	0.0515		19	-0.139	52.171	52.171	0.000
2	0.002	0.0537	0.0537		20	-0.159	64.484	64.484	0.000
3	-0.039	0.5671	0.5671		21	0.019	65.459	65.459	0.000
4	-0.070	2.1411	2.1411		22	-0.043	65.474	65.474	0.000
5	-0.080	4.1287	4.1287		23	0.026	66.211	66.211	0.000
6	0.232	22.176	22.176	0.000	24	-0.059	66.825	66.825	0.000
7	-0.076	23.877	23.877	0.000	25	-0.042	70.643	70.643	0.000
8	-0.045	24.137	24.137	0.000	26	0.078	70.803	70.803	0.000
9	-0.015	24.307	24.307	0.000	27	-0.039	70.816	70.816	0.000
10	0.103	26.048	26.048	0.000	28	-0.010	70.850	70.850	0.000
11	0.016	26.059	26.059	0.000	29	-0.051	70.879	70.879	0.000
12	-0.117	26.409	26.409	0.000	30	0.055	70.922	70.922	0.000
13	0.077	26.869	26.869	0.001	31	-0.035	72.779	72.779	0.000
14	-0.069	29.537	29.537	0.001	32	0.000	73.884	73.884	0.000
15	-0.040	30.361	30.361	0.001	33	0.036	74.092	74.092	0.000
16	0.138	40.535	40.535	0.000	34	-0.107	74.092	74.092	0.000
17	0.100	43.284	43.284	0.000	35	0.019	74.101	74.101	0.000
18	0.192	50.751	50.751	0.000	36	-0.002	74.132	74.132	0.000

To justify the goodness of fit of the chosen model($ARMA\ (2,3)$), the reports of performance metric (Mean Absolute Percentage Error also MAPE) and histogram of the residuals of the model were examined. The in-sample computed value of this metric is 2.54% and this indicated that error of forecast is within 10 percent error. Furthermore, the model yielded MAPE of 0.178 for out of sample forecast. Additionally, a good model is one where the coefficient of determination (R^2) is less than Durbin Watson (DB) (Onasanya & Adeniji, 2013) and the values of these statistics based on $ARMA\ (2,3)$ are respectively 0.8478 and 2.002. It is clear that the R^2 is lower than the DB confirming the goodness of fit of the $ARMA\ (2,3)$. However, Ljung-Box Q-Statistics highlighted that the hypothesis that the Residuals are non-random is not rejected at 5% level of significance for lag 6 through lag 36.
Likewise, it can be deduced from Figure 5 that the residuals based on $ARMA(2,3)$ are normally distributed as the bars of the histogram shown symmetric pattern indicating the fitness of the selected model to the underlying process.

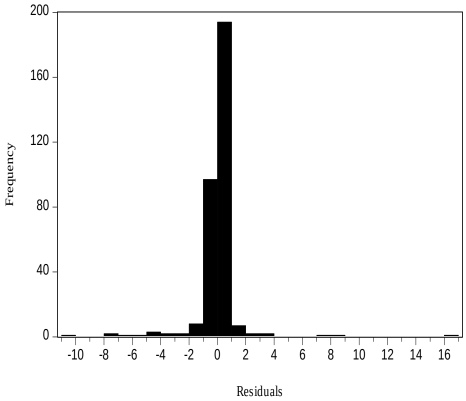

Figure 5. Histogram of Residuals based on $ARMA\ (2,3)$

5. Results and Discussions

The Naira – US Dollar Exchange Rates series is subjected to stationarity test by using three different approaches, namely: Augmented Dickey – Fuller (ADF) Test, runs sequence plot and Correlogram and in either case the series turned out stationary at level. On a quantitative note, this claim could be clearly seen from the fact that ADF Statistics presented in Table 1 are less than the test critical values at the significance levels of 1%, 5% and 10% with exceptional case at level without intercept and trend, meaning that the process is not a random walk. This result is further highlighted by the runs sequence plot (Figure 1) as it contains neither time variant trend nor seasonal cycles and a rapidly decayed Correlogram structure of the series at level as depicted in Figure 2. This finding is in agreement with the discovery that the Naira to Dollar assumes ARIMA (1,0,0) as opined by (Nwankwo, 2014). However, this discovery is contrary to the findings reported by (Onasanya & Adeniji, 2013), where the monthly Naira – US Dollar exchange rates series tends to be moving with time, which indicates that the parity series is non-stationary. Since the process is stationary at level, it can be concluded that the process could be best fit by ARMA (p, q). It can be observed that the parsimonious model is ARMA (2, 3) since it exhibited less BIC value of 3.977915 and the mathematical structure is given in equation (2). The model is unalike with models reported by (Nwankwo, 2014) and (Onasanya & Adeniji, 2013) because they respectively identified ARIMA (1,0,0) and ARIMA (1,2,1) as suitable models for forecasting the Naira – US Dollar exchange rate. This dissimilarity may be attributed to the policy shift, which is the basis of this research. An examination of the goodness of fit of the selected model based on performance metric (Mean Absolute Percentage Error) indicated that the error of forecast is within 10 percent. This implies that the model exhibit high accuracy and this claim is in line with the classification: MAPE values under 10% as high accuracy (Akincilar et al., 2011). The computed value of this metric is 2.54%. The measure also correlated with the findings of (Tlegenova, 2015), who reported that the MAPE was 4.45 per cent for US dollar, 4.64 percent for euro, and 3.69 percent for Singapore dollar rates all against Kazakh tenge. Similarly, (Nwankwo, 2014) discovered that ARIMA(1,0,0) is suitable for forecasting the yearly Naira-US Dollar parity. He further stated that the residual is negligible based on the identified model. Additionally, (Abdullah, 2012) reported that ARIMA (2, 1, 2) turns out model with error of forecast less than 10 percent. He also noted that the measure indicates that the forecasting of gold bullion coin selling prices inaccuracy is low. Furthermore, the model yielded MAPE of 0.178 for out of sample forecast. Nevertheless, the residuals based on $ARMA\ (2,3)$ are normally distributed as the bars of the histogram (Figures 5) displayed symmetric pattern. However, Ljung-Box Q-Statistics highlighted that the hypothesis that the residuals are non-random is not rejected at 5% level of significance for lag 6 through lag 36 in line with the existence of serial correlation in the exchange rates series of interbank market as discovered by (Emenike, 2016). Further suitability of the selected model is evident from the fact that the coefficient of determination (R^2) is less than Durbin Watson (DB). This finding is in line with opinion that a good model is one where the R^2 is less than DB (Onasanya & Adeniji, 2013) and the values of these statistics based on $ARMA\ (2,3)$ are respectively 0.8478 and 2.002.

6. Conclusion

This paper investigated official daily data of interbank market exchange rates of Naira/US Dollar made available by the Central Bank of Nigeria at www.cbn.gov.ng between July 1, 2016 and October 25, 2017. Conclusively, the findings of the investigation revealed that the future daily exchange rate of Naira per US Dollar may hinge on its past rates and associated innovations. It is found that $ARMA(2,3)$ is adequate and sufficient for forecasting the future parity between the two currencies. However, the non-randomness of the residuals based on Ljung – Box test and the percentage of variations explained (84.78%) by the past rates and innovations on the basis of $ARMA(2,3)$ may be regarded as suggestion to consider other models than ARMA for modelling the Naira-US Dollar parity, hence the need for further investigation.

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