International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438

A Suitable Model for the Forecast of Exchange Rate in Nigeria (Nigerian Naira versus US Dollar)

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Abstract: ***This project presents an empirical study of modeling and forecasting time series data of the official Exchange rate of Nigeria Naira to the US Dollar. The Box-Jenkins ARIMA and ARMA methodology were used for forecasting the monthly data collected from January 2000 to December 2012. Result analysis revealed that the series became stationary at first difference. The diagnostic checking has showed that ARIMA (1, 1, 2) and ARMA (1, 1) are appropriate or optimal model based on the Akaike's information criterion (AIC), Shcwarzt information criterion (SIC), and Hannan Quinn criterion (HQC). The performance of the models (ARIMA and ARMA model) for both in-sample and out-of-sample also show that ARIMA (1, 1, 2) has Minimum Mean Error (ME), Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), which indicates that ARIMA (1, 1, 2) model is the best or optimal model for the period forecasted .These forecasts would be helpful for policy makers in Nigeria to foresee ahead of time the Exchange rate, and the possible fluctuation intervals of Nigerian Naira to the US Dollar for future forecasted***

Keywords: ARIMA, ARMA Unit root Naira and US Dollar

1. Background of the Study

Exchange rates have become unfavorable to Nigeria as a result of using the floating foreign exchange determination system. Prior to 1986 Nigeria was on a fixed exchange rate determination system. At that time, naira was very strong in reference to dollar. The exchange rate was one naira to one US dollar i.e. N1=$1. The increasing demand for foreign exchange and the inability of the exchange control system to evolve an appropriate mechanism for foreign exchange allocation in consonance with the goal of internal balance made it to be discarded in September 26, 1986 while a new mechanism was introduced under the Structural Adjustment Programmed (SAP). The main objectives of the new exchange rate policy were to preserve the value of the domestic currency, maintain a favorable external balance and the overall goal of macroeconomic stability and to determine a realistic exchange rate for the Naira.

Since 1986 when the new exchange rate policy has been adopted, however, exchange rate determination in Nigeria has gone through many changes. Before the establishment of the Central Bank of Nigeria in 1958 and the enactment of the Exchange Control Act of 1962, foreign exchange was earned by private sector and by commercial banks that acted as agents for local exporters. The boom experienced in the 1970s made it necessary to manage foreign exchange rate in order to avoid shortage. However, shortages in the late 1970s and the early 1980's compelled the government to introduce some ad hoc measures to control excessive demand for foreign exchange. However, it was not until 1982 that comprehensive exchange controls were applied. These lists include the fixed exchange rate, the freely floating and the managed floating system among others. In an attempt to achieve the goal of the new exchange rate policy, a transitory dual exchange rate system (First and Second –Tier – SFEM) was adopted in September, 1986, but metamorphosed into the Foreign Exchange Market (FEM) in 1987. Bureau de change was introduced in 1989 with a view to enlarging the scope of FEM. In 1994, there was a policy reversal, occasioned by the non-relenting pressure on the foreign exchange market. Further reforms such as the formal pegging of the Naira exchange rate, the centralization of foreign exchange in the CBN, the restriction of Bureau de change to buy foreign exchange as an agent of CBN etc. were all introduced in the foreign exchange market in 1994 as a result of the volatility in exchange rates. Still, there was another policy reversal in 1995 to that of "guided deregulation". The Dutch Auction System was reintroduced in 2002 as a result of the intensification of the demand pressure in the foreign exchange market and the persistence in the depletion of the country's external reverses.

Finally, the wholesales Dutch Auction System (W-DAS) was introduced in February 20, 2006. The introduction of the WDAS was also to deepen the foreign exchange market in order to evolve a realistic exchange rate of naira.

2. Literature Review

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. Leseps and Morell (1977) in their study found that the exchange rate follows a long-term trend with short-term fluctuation. 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. Pagan and Schwert (1990) found evidence that ARIMA models performed well when compared to nonparametric and Markov switching models.

Schmitz and watts (1970) used parametric modeling to forecast wheat yields in the United States, Canada, Australia and Argentina. 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.

Lirby (1966) compared three different time-series methods viz., moving averages, exponential smoothing, and regression. He found that in terms of month-to-month forecasting, horizon was increased to six months. The regression models included was found to be the best method for longer-term forecasts of one year or more. Sleckler found that econometric models were not entirely successful in improving the accuracy in forecasting.

Leuthold et.al (1970) in their study of forecasting daily hog price and quantities' used Theil's inequality coefficient for comparing the predicative accuracy of the different forecasting approaches.

3. Methodology

The formulation of ARIMA and ARMA model depends on the characteristics of the time series. The data will be modeled using Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Moving Average ARMA model, popularized by Box and Jenkins (1976). An ARMA (p, q) model is a combination of Autoregressive (AR) which shows that there is a relationship between present and past values, a random value and a Moving Average (MA) model which shows that the present value has something to do with the past residuals. The ARMA (p, q) process can be defined as follows;

3.1 Autoregressive Model

The notation AR (p) refers to the autoregressive model of order p. the AR (p) model is written as

$$Y_t = C + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \varepsilon_t , \qquad (1)$$

Where $\varphi_1, \dots \varphi_p$ are parameters, C is a constant and the random variables ε_t is white noise (error term).

3.2 Moving – Average Model

The notation MA (q) refers to the moving average model of order q.

$$Y_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \text{ , t} = 1{,}2 \dots \qquad (2)$$

Where $\theta_{1,\dots,}\theta_q$ are parameters, μ is the expectation of Y_t and ε_t is white noise (error term).

3.3 ARMA (p, q) Model

The notation ARMA (p, q) refers to the model with p autoregressive terms and q moving- average terms. Finally, by combining equation 3.01 and 3.02 the ARMA (p, q) is given by

$$Y_t = C + \varepsilon_t + \sum_{i=1}^{p} \varphi_i + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \qquad (3)$$

To achieve the above mentioned, there are three steps namely;

I. Model identification
II. Model estimation
III. Model verification or diagnostic checking.

3.3 Model Identification

Model identification involves examining the given data by various methods, to determine the values of p, q, and d. The values are determined by using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). This can be done by observing the graph of the data or autocorrelation partial autocorrelation functions (Makridakis et, al 1998). For any ARIMA (p, d, q) process, the theoretical (PACF) has non-zero partial autocorrelation at 1, 2… p and has zero partial autocorrelations at all lags. While the theoretical (ACF) has non-zero autocorrelation at all lags. The non-zero lags of the sample PACF and ACF are tentatively accepted as the p and q parameters. For a non stationary series the log data is differenced to make the series stationary. The number of times the series differenced determines the order of d. thus, for a stationary data d=0 and ARIMA (p, d, q) can be written as ARMA (p, q).

3.3 Model Estimation

After an optimal model has been identified, the model estimation methods make it possible to estimate simultaneously all the parameters of the process, the order of integration coefficient and parameters of an ARMA structure. The estimators of the exact maximum likelihood proposed by sowell is the vector $\hat{\beta} = (\hat{d}, \hat{\varphi}, \hat{\theta})$ which maximizes the log likelihood function L (β).

$$L(\beta) = -(\tfrac{n}{2}) \ln(2\pi) - \left[\tfrac{1}{2}\right] \ln(R) - \left[\tfrac{1}{2}\right] X'R^{-1}x \quad (4)$$

Where R is the variance – covariance matrix of the process

3.4 Model Verification

The last step is model verification or model diagnostic check, and involves assessing the residuals of the model to determine whether to accept the model or reject it. For methods of residual assessment, if evidence results in letter case, whether it is from inadequacies of the model, or availability of additional data, the model building process will need to be repeated from step 2, or even step 1. Repeating of this process may occur many times before a model is finally decided upon. Thus model building is an iterative, interactive process.

So, given multiple completing models, we decide upon a final one model which is one popular method to use a model selection criterion; Akaike's Information Criterion (AIC) Schwartz information Criterion (SIC) and Hannan Quinn Criterion (HQC) which attempts to choose a mode that adequately describes the data but in the most parsimonious way possible, or in other words, minimizing the number of parameters. For example, if an AR (2) model doesn't outperform AR (1) by a certain predefined quantity or criteria, then AR (1), the model parsimonious model, is choose In general, the model that is chosen is the one that minimizes the respective criterions score.

3.4.1 Akaike's Information Criterion

Akaike's Information Criterion (AIC) originally proposed by Akaike, attempts to select a good approximating model for inference based on the principle of parsimony. AIC proposes the use of the relative entropy, or the Kull back –Leibler (K-L) information as a fundamental basis for model selection. A suitable estimator of the relative K-L information is used and involves two terms. The first tem is a measure of lack of model fit, while the second is a "penalty" for increasing the size of the model, assuring parsimony in the number of parameters. The AIC criterion to be minimized is

$$\text{AIC}(n) = \log(\delta_q^2) + \frac{2n}{T} \quad (5)$$

Where n is the dimensionality of the model, δ_q^2 is the maximum likelihood estimate of the white noise variance, and T is the sample size.

3.4.2 Schwarz's Bayesian Information Criterion

The Bayesian Information Criterion (BIC), originally proposed by Schwarz was derived in a Bayesian context and is "dimension consistent" in that it attempts to consistently estimate the dimension of the true model. It assumes a true model exists in the set of candidate models, therefore requires a large sample size to be effective. The BIC Criterion to be minimized is

$$\text{BIC}(n) = \log(\delta_q^2) + \frac{n\log(T)}{T} \quad (6)$$

Where n is the dimensionality of the model, δ_q^2 is the maximum likelihood of estimate of the white noise variance, and T is the sample size.

3.4.3 Hannan – Quinn Criterion

The Hannan – Quinn (HQ) Criterion, originally proposed by Hannan and Quinn was derived from the low of the iteration logarithm, it is another dimension consistent model and only differs from AIC and BIC with respect to the "penalty term". The HQ Criterion to be minimized is

$$\text{HQ}(n) = \log(\delta_q^2) + \frac{2n\log(T)}{T} \quad (7)$$

Where n is the dimensionality of the model, δ_q^2 is the maximum likelihood of estimate of the white noise variance, and T is the sample size. Hannan and Rissanen later replaced the term log log (n) with log n to speed up the convergence of HQ

3.5 Tests for stationarity

First, we have to test the stationary of the time series. We can use scatter plots or get an initial idea of the problem. But the formal and the most popular method to test the stationary of a series is the unit root test. This is the test that is used to carry out or to know the order of integration of non-stationary variable, so there may be difference before being included in a regression equation. The most common unit root tests are:

1. The Augmented Dickey Fuller (ADF) test.
2. And the Phillilps – Perron (PP) test.

3.5.1 Augmented Dickey fuller test

Fuller: The test was first introduced by Dickey and Fuller (1979) to test for the presence of unit root(s). The regression model for the test is given as

$$\boldsymbol{\Delta y_t = \gamma y_{t-1} + \beta x_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \dots + \delta_p \Delta y_{t-p} + \varepsilon_t} \quad (8)$$

The hypothesis testing

$H_0 : \gamma = 0$ (the series contain unit root(s))

$H_1 : \gamma < 0$ (the series is stationary)

Test statistic

$$t_\gamma = \frac{\gamma}{s_e(\gamma),} \quad (9)$$

Where

Δy_t = the difference series

y_{t-1} = the immediate previous observation

$\delta_{1,\dots,}\ \delta_p$ = the coefficient of the lagged difference term up to p

x_t = the optimal exogenous regresses which may be constant or constant Trend

γ And β = parameters to be estimated.

Decision rule:

Reject H_0 if t_γ is less than asymptotic Critical values

3.5.2 Phillips – Perron test:

Phillips and Perron (1988) pressed a non-paramateric method of the controlling the higher-order series correlation in a series.

The test regression for the Phillips-Perron (PP) test is the AR (1) process;

$$\Delta y_t = \alpha + \beta y_{t-1} + \varepsilon_i \quad (10)$$

The hypothesis testing:

$H_0 : \beta = 0$ (the series contains unit root)

$H_1 : \beta < 0$ (the series is stationary)

Test statistic

$$\tau_{\hat{\beta}} = t_{\hat{\beta}} \left(\frac{\gamma_0}{f_0}\right)^{1/2} - \frac{T(f_0 - \gamma_0)(s_e(\beta))}{2 f_o^{1/2} s} \quad (11)$$

$$\gamma_o = \frac{(T-K)s^2}{T},$$

Where
$\hat{\beta}$ = the estimate parameter
t_{β} = the t – ratio of β
$s_e(\hat{\beta})$ = the coefficient standard error
S = the standard error of the last regression
γ_o = the consistent estimate of the error variance.
f_o = the estimator of the residual spectrum at frequency zero.
Decision rule:
Reject H_0 if τ_{β} is less than the asymptotic critical value

4. Data Analysis

In this chapter we shall use the monthly official exchange rate in Nigeria to identify and estimate ARIMA and ARMA model that fit the series and use some diagnostic tests to evaluate the model. The data set is from Nigerian official exchange rate for the naira and US dollar, for the period from January 2000 to December 2012.

4.1 Graphical presentation of the exchange rate data

We begin with the investigation of the time plot of the series in levels.

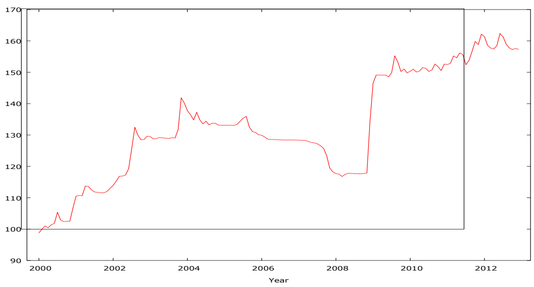

Figure 1: Time plot of the monthly exchange rate of naira to us dollar from January 2000 to December 2012.

From the plot we observed that the mean is not constant (i.e. is changing with time). And also from this plot we can see that the exchange rate varies a lot. It seems that the exchange rates do not move stably. Primarily we doubt the stationary of the time series.

4.2 ACF and PACF of the series (ARIMA MODEL)

Having observed from the time plot that the mean of the series is changing with time, next we examine the autocorrelation functions (ACF) and partial autocorrelation function (PACF) to see if there exist correlations in data points of the series.

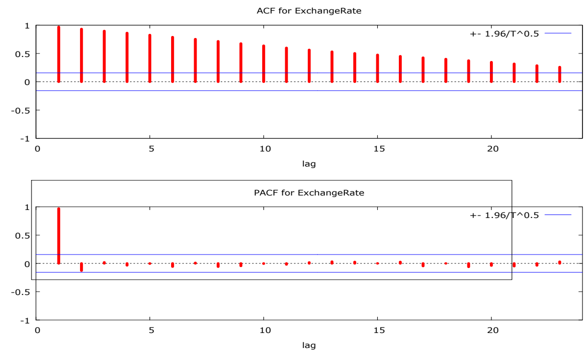

Figure 2: ACF and PACF of monthly exchange rate of Naira and US dollar from January 2000 to December 2012

We observed that from figure 4.02 plots that, the series decay geometrically, that is autocorrelation function (ACF) start high and declined slowly, and partial autocorrelation (PACF) dies to zero after the first lag, which also confirms the presence of low order serial dependency in the series. This shows that the series is non-stationary, should be differenced. Next we perform the unit root test to check the stationary of the series.

4.3 Unit root tests

Two tests (ADF and PP) were carried out to test for the presence of the unit root(s) in the series. The ADF statistic tests the null hypothesis of the presence of the unit root against the alternative of no unit root. The decision rule is to reject the null hypothesis when the value of the test statistic is less than the critical value. From the result in table 4.01, the ADF test statistic was found to be -1.473382, the value is greater than the critical value, and hence we cannot reject the null hypothesis of unit root.

The phillip- perron test is non parametric (using estimate of the spectrum of the residual) method of controlling for higher order serial correlation. As in ADF, the statistic tests the null hypothesis of presence of unit root against the alternative of no unit root. The decision rule is to reject the null hypothesis when the value of the test statistic is less than the critical value. Also from the result in table 4.01, The PP test statistic was found to be -1.503159. Again this value is greater than the critical value and from the two results we conclude that the series is non stationary. Next we determine the order of integration of the series. We take the first differencing the series and repeat the test.

Table 1: Result of ADF and PP Test in Level

ADF & PP Test in Level

Test	Test Stat	Mackinnon Critical Values
ADF	-1.473382	1% -3.473382 5% -2.880336 10% -2.576871
PP	-1.503159	1% -3.472813 5% -2.880088 10% -2.576739

Table 2: ADF and PP in difference

ADF & PP Test in first Difference

Test	Test stat	Mackinnon Critical Values
ADF	-8.529864	1% -3.473431 5% -2.881345 10% -2.577811
PP	-8.381783	1% -3.473096 5% -2.880211 10% -2.576805

4.4 Choice of the best model

Once stationary have been addressed, the next step is to identify the order (the p, d, and q) of the autoregressive and moving average terms. The primary tools for doing this are: Akaike information criterion, schwatz information criterion, and Hannan Quinn information criterion. That is the model that gives minimum A

4.4.1 ARIMA MODEL IDENTIFICATION

Table 3: below gives some selected models to test.

MODEL	AIC	SIC	HQC
ARIMA (1, 1, 1)	702.8552	715.0030	707.7896
ARIMA (2, 1, 1)	699.4491	714.6339	705.6171
ARIMA(1,1,2)*	696.772*	711.957*	702.940*
ARIMA (3, 1, 1)	700.7536	718.9754	708.1553

From table 4.02 we observed that the optimal model is ARIMA (1, 1, 2) that is based on the selection criterion AIC, BIC, HQC. *= best.

4.4.2 ARMA MODEL identification

Table 4: some selected models to test.

MODELS	AIC	SIC	HQC
ARMA(1, 1)*	705.6993*	717.898*	710.6542*
ARMA(1, 2)	707.1727	722.4220	713.3663
ARMA(2, 1)	707.0253	722.2746	713.2189

The asterisks above indicate the best model or optimal model (that is minimized) value of the respective information criteria, Akaikes information criterion (AIC), Schwartz information criterion (SIC), Hannan Quinn criterion (HQC) model or optimal model.

4.5 Model estimation

After an optimum model has been identified, the model estimation methods make it possible to estimate all the parameters of the process, the order of integration coefficient and the parameters of an ARIMA and ARMA structure.

4.5.1 ARIMA Model Estimation

Table 5: The estimated model

Model 1: ARIMA, using observations 2000:03-2012:12 (T = 154)
Estimated using Kalman filter (exact ML)
Dependent variable: Exchange Rate
Standard errors based on Hessian

	Coefficient	Std error	p-values
Const	-0.00234335	0.0542909	0.6660
Phi_1	-0.179699	0.170849	0.2929
Theta_1	-0.382868	0.140754	0.0065***
Theta_2	-0.617132	0.139818	1.02e-05***

Mean dependent var -0.009545
S.D. dependent var 2.789278
Mean of innovations -0.043500
S.D. of innovations 2.215783
Log-likelihood -343.3862
Akaike criterion 696.7724
Schwarz criterion 711.9571
Hannan- Quinn 702.9404

4.5.2 ARMA Model Estimation

Table 6: The estimated model

Model 1: ARMA, using observations 2000:01-2012:12 (T = 156)
Estimated using kalman filter (exact ML)
Dependent variable: Exchange Rate
Standard errors based on Hessian

	Coefficient	Std error	p-value
Const	130.087	16.5215	‹0.00001***
Phi_1	0.989098	0.0111393	‹0.00001***
Theta_1	0.481442	0.0788082	‹0.00001***

Mean dependent var	132.7062	***
Mean of innovations	0.071156	***
Log-likelihood	-348.8496	***
S.D. dependent var	16.93388	
S.D. of innovations	2.229230	
Akaike criterion	705.6993	
Hannan-Quinn	710.6542	

4.6 ARIMA and ARMA Model evaluation

We use diagnostic tests of the model residuals to check if the model has adequately fitted the series. First, we check to see if there exist serial correlations in the residual. We specifically performed the portmanteau test, and observed the plots of the ACF and PACF. Next we use the jarque-Bera test for normality to test whether the residuals are normally distributed.

Table 7: portmanteaus and Normality test

	Type of test	Test stat	p-value
ARIMA MODEL	Ljung–Box Skewness Kurtosis	17.03 3.31 16.226	0.827 0.6499 0.6499
ARMA MODEL	Ljung-Box Skewness Kurtosis	43.810 3.0157 16.003	0.62115 0.6594 0.6594

The results in the TABLE above accept the null hypothesis since p-value is greater than the critical value.

4.6.1 ACF and PACF of the residuals

Next we plot the ACF and PACF of the standardized residuals to visually see if there exist autocorrelation. The graphs are plotted using 20 standardized residuals and in as much as there is no point outside the confidence limit (∝ = 0.05) the residual are uncorrelated

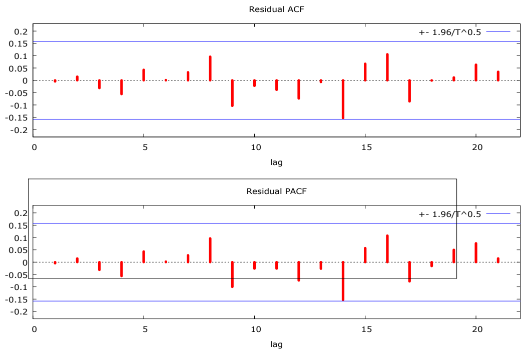

Figure 3: ACF and PACF of the residuals

Figure above show no evidence of serial correlation in the residuals and hence the model is adequate.

4.7 ARIMA and ARMA Model Forecast Performance

We compute forecast error statistics in order to assess the performance of the forecast. In particular we compute mean error (ME) mean squared error (MSE) root mean squared error (RMSE) mean absolute error (MAE) using forecast and actual values for both in- sample and out- sample data. The smaller the mean squared error the better the performance. The results of the computations are presented in the tables below:

Table 8: in – sample error performance of the model

	ARIMA MODEL	ARMA MODEL
ME	-0.040072	0.29471
MSE	5.2667	12.521
RMSE	2.2949	3.5386
MAE	1.6104	1.6768

Table 9: out-of-sample error performance of the model

	ARIMA Model	ARMA Model
ME	-0.062068	0.03051
MSE	3.7538	3.8772
RMSE	1.9375	1.9691
MAE	1.2322	1.3104

We observed from tables 4.1- 4.2 that the performance of the in- sample data has bigger ME, MSE, RMSE, MAE than the out -of- sample data for both ARIMA and ARMA Model. This result suggests that the forecast for the in-sample has smaller difference with the actual data than the out-of-sample forecast.

4.8 ARIMA and ARMA Model Forecast Evaluation

The full sample is from January 2000 to December 2012. To test which predicting method is better, we choose data from January 2000 to December 2010 to build up the prediction function. Then we use the data from January 2011 to 2016 December out-of-sample forecast. The visual plots are presented below.

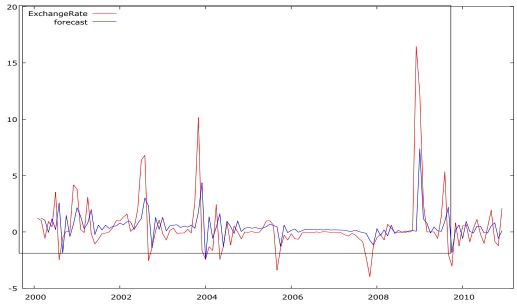

Figure 4: plot of the in-sample actual versus predicted values from 2000:01 to 2010:12

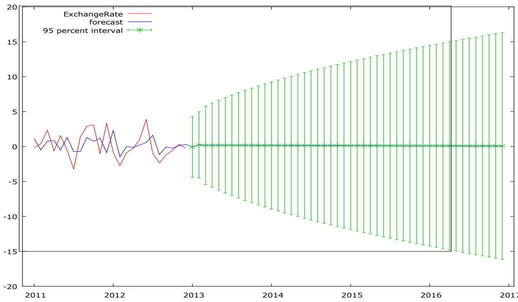

Figure 5: plot of the out-sample actual versus predicted values from 2011:01 to 2016:12

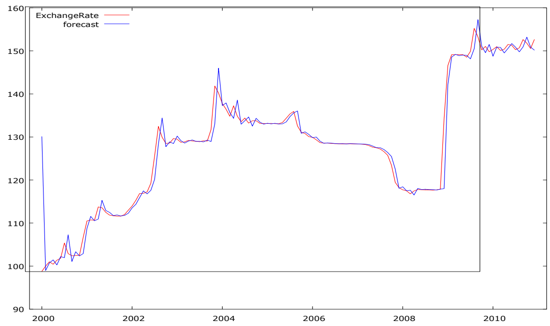

Figure 6: plot of the in-sample actual versus predicted values from 2000:01 to 2010:12

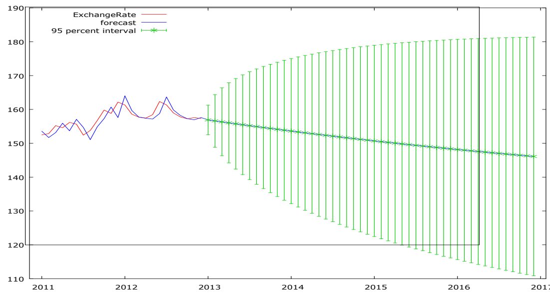

Figure 7: plot of the out-sample actual versus predicted values from 2011:01 to 2016:12

We also observed from figure above that the interval lines are within the confidence limit suggested that exchange rate will continue to be unstable for the period forecasted.

4.9 Comparison of the Two Models (ARIMA and ARMA MODELS)

Table 10: prediction/forecasting error values of the two models

Error	ARIMA (1, 1, 2)	ARMA (1, 1)
ME	-0.062068	0.03051
MSE	3.7538	3.8772
RMSE	1.9375	1.9691
MAE	1.6104	1.6519

The purpose of this study is to search the best predictive performance model among the competitive models. Table 4.17 shows the error values for all the two models. Mean Error (ME) Mean Absolute Error (MAE), Mean Squared error (MSE), Root mean square error (RMSE) are some of the frequently used measures of forecast adequacy. The rule of thumb is the smaller ME, MAE, MSE and RMSE, the better is the forecasting ability of that model. The ME, MAE, MSE and RMSE associated with ARIMA model is the smaller, compare with other model. Therefore, it is proposed that ARIMA model is the best or optimal model among the other model.

5. Summary and Conclusion

We used ARIMA and ARMA model to estimate the data that best describe the monthly official exchange rate in Nigeria. The data set is from monthly official exchange rate for the naira to US dollar for the period from January 2000 to December 2012. Result analysis revealed that the series became stationary at first difference. Further analysis showed that among all the class of ARIMA and ARMA model based on Akaike's information criterion (AIC), schwarzt information criterion (SIC) and Hannan Quinn criterion (HQC), the best or optimal model was ARIMA (1, 1, 2) and ARMA (1, 1). The performance of the model for both in-sample and out-of-sample shows that ARIMA (1, 1, 2) has the minimum ME, MSE, MAE, RMSE which indicate that ARIMA (1, 1, 2) model is the best or optimal model for the period forecasted.

This study has assessed comprehensively and systematically the predictive capabilities of the exchange rate forecasting models. To obtain the generality of the empirical results, ARIMA, ARMA model have been compared. Some of the frequently used measures of forecast adequacy such as Mean Error (ME), Mean Absolute Error (MAE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) were used to evaluate the forecast performance of the chosen models. This study reveals the fact that ARIMA methodology produces superior results than ARMA models.

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