DATA TRANSFORMATION AND ARIMA MODELS: A STUDY OF EXCHANGE RATE OF NIGERIA NAIRA TO US DOLLAR

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Abstract: Exchange rate of any country's currency goes a long way in affecting various economic activities and it ensures effective and efficient planning. In order to assist different policy makers in Nigeria in purposeful prediction by identifying and validating the usage of essential model, the yearly average exchange rate of Nigeria naira to US dollar from 1960 to 2015 is examined. ARIMA (0,0,0 to 2,2,2) were sequentially examined using Square Root Transformation (SRT), Natural Log Transformation (NLT) and original series without transformation (WT). NBIC, RMSE, MAE, and Ljung-Box Q are used as selection criteria among all the competing models within and among different transformations. ARIMA(1,0,0) when SRT is utilized is found to provide optimal output with stationary-R^2 of 0.976; coefficient of determination (R^2) of 97.3%; NBIC of 4.888 and Ljung-Box Q P-value of 0.981. Hence, the recommended model for forecasting of average yearly exchange rate of Nigeria naira to US dollar.

Keywords: Time series, ARIMA model, natural log transformation, square root transformation.

Introduction

The rate of exchange of a country's currency is the relative price which measures the value of a domestic currency in terms of another currency, (https://en.wikipedia.org/wiki/Exchange_rate). Because of inherent structural transformations required, exchange rate policies in developing and under-developed countries are usually sensitive and controversial. When there is a very high disparity in the balance of trade of any country, the exchange rate is usually affected. The effect becomes so obvious and negative when such country is a consuming nation rather than a producing one. Guitan (1976) reported that the "for any currency depreciation towards promoting balance of trade to succeed, it must depend on switching demand in proposer direction and the economy must have capacity to meet additional demand by ensuring supply of more goods". Effectiveness and efficiency of an economy are usually determined by fluctuations of exchange rate. Hence, attaching importance to planning economic policies based on the predictions of exchange rate is necessary.

Exchange rate policy in Nigeria has gone through numerous transformations since her independence when there was a fixed parity with the British Auctions System (BAS) as against the former auctions done once two weeks which assured a relative steady supply of foreign exchange. The Central Bank of Nigeria (CBN) introduced the Wholesale Dutch Auction System (WDAS) in 2006 with intention to liberalize the money market, reduce the arbitrage premium between the Bureaus de Change (BdC) operators and the interbank officials. The purpose of the introduction is to consolidate gains recorded when CBN was using the Retail Dutch Auction System (RDAS) and also to deepen the foreign exchange market in order to reveal a realistic exchange rate of the naira. This process gave room for dealers that are authorized to deal in foreign exchange using their respective accounts before selling to their customers.

One of the leading demands of modern time series analysis and forecasting is exchange rate prediction. The exchange rates are naturally non-stationary, deterministically chaotic, and noisy, Box and Jenkins (1994). It fluctuates and requires adequate statistical technique that can consider adequately represent the variability. In order to have a better understanding of the underlying process, the fluctuations are usually examined with a class of structural time series models with intention of obtaining estimates that are more efficient. The importance of optimal model of any economic variable cannot be over emphasized. Both developed and developing countries need these models for effective management of often limited resources and effective planning. Usually, there are always sets of competing models that may be seen to be equally effective and efficient when being applied to a particular data set. The interest then is to find out which particular one among these models will give be the best and most efficient (optimal) taking into consideration all the essential factors.

Different approaches have been developed for forecasting time series data and there are competitions among these methods on efficiency and minimal error while forecasting. Among widely used techniques is the Autoregressive Integrated Moving Average (ARIMA) where a time series is expressed in terms of its past values and lagged values of error term. There are variations of ARIMA models that can be employed depending on the nature of the data to be analyzed. If there are multiple time series data, then the $\boldsymbol{X_t}$ can be assumed to be vectors and a (Vector ARIMA) VARIMA model may be appropriate. When a seasonal effect is suspected in the model, a Seasonal ARIMA (SARIMA) model can be used. If the there is a suspicion that the series exhibits a long-range dependence, then the Autoregressive Fractionally Integrated Moving Average model (ARFIMA) which is also called a Fractional ARIMA (FARIMA) model may be used.

This paper varies parameters of ARIMA model under different transformations with the purpose of observing their efficiency in purposeful forecasting. In economic time series, transformation is often considered to stabilize the variances of the series, hence, this research compares various results forecasting based on the original series (0,0,0 to 2,2,2) with both its square root transformations (SRT) and natural log transformations (NLT). For NLT, let $X_t = \log Y_t$ be the natural logarithm of the time series data, X_t is then used to generate an ARIMA model while $X_t = \sqrt{Y_t}$ for the SRT.

Little or no attention has been given to effect of data transformation when researching into exchange rate of Naira to Dollar, Onasanya & Adeniji (2013) and Nwakwo (2014). Granger and Newbold (1976) opined that optimal forecast may not be obtained when an instantaneous non-linear transformation is applied to a variable while Lϋtkepohl and Xu (2009) stated that substantial reduction in error may be committed in forecast Mean Squared Error (MSE) if the log transformation can lead to a more stable variance of a series of interest but warned that forecasting prediction may be damaged when the log transformation is applied and it does not make the variance more homogeneous.

Application of ARIMA models in diverse studies of interest is inexhaustible. Various researches had been carried out for different scenario using the Box-Jenkins approach. While forecasting the exports of Pakistan's South Asian Association of Regional Cooperation (SAARC), Shafaqat (2012) applied the Box-Jenkins methodology of univariate ARIMA model and found ARIMA (1,1,4) as most appropriate model among other tested ARIMA models. The study revealed that exports from Pakistan to SAARC will be on the increase in a few years and hence the need for Pakistani government to invest into those sectors in which the country has export potential to the SAARC countries.

While predicting next day process of electricity for Spain and California (Contreras *et al.,* 2003) used ARIMA model and it was observed that the Spanish model requires 5 h to forecast for future prices which opposes 2 h needed with the Californian model. Tsitsika *et al*. (2007) adopted ARIMA model in forecasting pelagic fish production. The ARIMA (1,0,1) and ARIMA (0,1,1) were adjudged to be optimal while Datta (2011) used ARIMA to forecast inflation rate in Bangladesh. The result of his analysis showed that ARIMA (1,0,1) is the best model that fits the inflation rate of Bangladesh.

ARIMA had also been applied in healthcare studies. Sarpong (2013) studied Maternal Mortality Ratios (MMR) in a Kumasi Teaching Hospital for 11 years. The result showed that the hospitals MMR was relatively stable with a very alarming average quarterly MMR of 9.677 per thousand live births which is almost twice the ratio obtained in the whole of Ghana (4.51 per thousand). AIC value of 581.41 made the researcher to conclude that ARIMA (1,0,2) is the most adequate model for forecasting quarterly MMR at the hospital (Liv *et al.,* 2011) as well utilized ARIMA model to forecast hemorrhagic fever incidence with renal syndrome in China, ARIMA (0,3,1) model was found to be the best for predictive purpose. Albayrak (2010) applied same model to forecast the production and consumption of primary energy in Turkey.

With intention of obtaining forecast values for the average daily price of share of Square Pharmaceuticals Limited (SPL), Jiban *et al.* (2013) examined ARIMA model by observing the conditions for the stationarity of the data series using ACF and PACF plots, and later used Dickey-Fuller test statistic and Ljung-Box Q-statistic. The result showed that the time series data is not stationary even after log-transformation but the series became stationary after taking the first difference of the log-transformation. RMSE, AIC and MAPE are used to select the most fitted ARIMA model, they concluded that the best model that nest describes the series is ARIMA (2,1,2). While using some measures such as: MAPE, RMSE and MAE for selection of appropriate model (Emang *et al.*, 2010) as well made use of ARIMA model in forecasting chipboard and moulding export demand in Malaysia. Rahman (2010) constructed an ARIMA model to forecast the production of rice in Bangladesh using MAPE, MSE, MAE, RMSE and R^2 as selection criteria.

In Nigeria, researchers had utilized ARIMA models for various purposes. Badmus and Ariyo (2011) used this model to forecast the production and area of maize from Nigerian. Adams, Akano, and Asemota (2011) also used this model to forecast generation of electricity power from Nigeria. They concluded ARIMA (3,2,1) is the best model. While applying ARIMA Model on rate of exchanging Naira to Dollar for a period of thirty years (1982-2011), Nwakwo (2014) concluded that AR(1) was the preferred model for purposeful prediction.

From various works of researchers, little effort had been given to effect of data transformation on forecasting and overall usefulness of ARIMA model. Hence, this paper is aimed at observing efficiency of ARIMA (p,q,d) under different transformations and using various measures like MAE, RMSE, and R^2 as selection criteria. This is expected to improve quality of decision by those involved in monetary policies formulation as it affects exchange rate.

Materials and Methods

Autoregressive integrated moving average (ARIMA) model is a general form of an autoregressive moving average (ARMA) model. The model is fitted to time series data with primary aim of having a better understanding of the series and to predict its future values, especially when the series shows signs of non-stationarity. The non-stationarity is often reduced by applying an initial differencing step (integrated). ARIMA models that are non-seasonal are usually denoted with ARIMA (p,d,q) where *p* implies the order of the AR model, *d* is the differencing degree and *q* represents the moving average order, Box and Jenkins (1994).

ARIMA model has a major advantage over majority of time series modelling since it utilizes data on the time series of interest only. This usually serves most when dealing with multivariate models where different factors might have affected the quality of the input variables. Although arguments in using ARIMA models among researchers persists, ARIMA models has been proved to be relatively robust most especially when dealing with short-term forecast. Glassman and Stockton (1987) verified the robustness of ARIMA models for short-term forecasting.

Autoregressive (AR) process

An AR process requires each value of a series to be a linear function of value preceding them. Hence, in an AR of order 1, only the first preceding value is utilized as a function of the current value. AR(1) denotes the first order AR scheme while AR(2) denotes its second order.

Suppose that the variable $\boldsymbol{Z_t}$ is a linear function of any preceding variable $\boldsymbol{Z_{t-1}}$, the model for an AR(1) can be written as:

$$Z_t = \theta + \varphi_1 Z_{t-1} + \varepsilon_t \quad \ldots\ldots\ldots (1)$$

where $\varepsilon_t \sim NIID(0, \sigma_\varepsilon^2)$

For an AR(2), the model becomes

$$Z_t = \theta + \varphi_1 Z_{t-1} + \varphi_2 Z_{t-2} + \cdots + \varphi_p Z_{t-p} + \varepsilon_t \ldots\ldots (2)$$

where $\varepsilon_t \sim NIID(0, \sigma_\varepsilon^2)$ and φ_p is the coefficient of first order AR while is the coefficient for p^{th} order AR.

Differencing

Procedure for differencing involves calculating series of sequential changes in the values of the time series data. It is usually used when there is a systematic change in the mean of the observation as the time changes. Differencing often ensures that a series that is not stationary becomes stationary with homogeneous variance. Differencing a series once requires calculating the periodic change once and to do it twice needs the calculation to be done twice.

Moving average (MA)

This is also known as the rolling average. It is usually applied in analysing financial data and can as well be used like a generic smoothing operation. MA series can be obtained for any time series data and are usually used to smoothen short-term fluctuations and therefore highlights a longer-term cycles.

Let the model Z_t be defined as:

$Z_t = \theta + \varepsilon_t + \beta_1\varepsilon_{t-1}$ ... ... (3)

where θ is constant and $\varepsilon_t \sim NIID(0, \sigma_\varepsilon^2)$.

Z_t is a constant added to a MA of the current and error terms in the past. Hence, Z_t is said to follow MA (1) process i.e. a moving average of order 1. But if Z_t is denoted with:

$Z_t = \theta + \varepsilon_t + \beta_1\varepsilon_{t-1} + \beta_2\varepsilon_{t-2}$ ... ... (4)

then Z_t is said to follow a MA(2) process.

Generally, Z_t follows a MA(q) process if

$Z_t = \theta + \varepsilon_t + \beta_1\varepsilon_{t-1} + \beta_2\varepsilon_{t-2} + \cdots + \beta_q\varepsilon_{t-q}$ ... ... (5)

ARIMA Model Selection, Checking and Validation

Model Selection

When an attempt is being made to use ARIMA model for predictive purpose, the first step is to identify the model that best explains the model. Such model should have smallest values of parameters and should be good enough to adequately explain the model. In ARIMA (p,d,q), p and q must not be more than 2, Al–Wadia (2011). Therefore, checking the NBIC (Normalized Bayesian Information Criterion) of the model is only limited to p, q and d values 2 or less. According to Al–Wadia (2011), the model that has the least NBIC value should be given preference. Another criterion often used to measure goodness of fit of a model is the Akaike Information Criteria (AIC). When two or more models are competing, the one that has the least AIC is generally considered to be closer with real data, Yang (2005). However, *Anderson (2008)* opined that AIC does not usually penalize complexity of a model heavily as the BIC (Bayesian Information Criterion) does.

Checking the model

Appropriate lag (the value of p) is usually identified using the autocorrelation function (ACF) and partial autocorrelation function (PACF). The PACF provides more information on the behaviour of the time series while the ACF provides information on the correlation between observations in a time series at different time apart. Both ACF and PACF suggest the model to be built. Generally, the ACF and the PACF has spikes at lag k and cuts off after lag k at the non-seasonal level. The order of the model can be identified by the number of spikes that are significant. It must be noted however that both ACF and PACF only suggest on where to build the model, it is very essential to obtain different models around the suggested order and criteria like Akaike Information Criterion (AIC), Akaike (1974) or Bayesian Information Criterion (BIC), Schwarz (1978) can then be used to select the best among the competing models.

The AIC and BIC are obtained using:

AIC = 2k – 2 log(L) = $2k + n\log\left(\frac{RSS}{n}\right)$ ... ... (6)

[https://en.wikipedia.org/wiki/Akaike_information_criterion]

BIC = -2 Log(L) + k Log(n) = $n\log(\sigma_e^2) + k\log(n)$ ... . (7)

[https://en.wikipedia.org/wiki/Bayesian_information_criterion]

k is the number of parameters in the model; L is the value maximized for the likelihood function for the estimated model; n is the number of observation i.e. the sample size; RSS is the residual sum of squares of the estimated model and is the error variance.

Model validity

In order to select the best among competing models, it is essential to compute some statistics that would ensure that the final model to be selected has the least variance. These criteria are compared for three periods viz, estimation period, validation period and total period. With respect to this research, the following selection criteria are used: (a) Mean Absolute Error (MAE), and (b) Root Mean Square Error (RMSE)

Mean absolute error (MAE)

This is the mean of the absolute deviation of predicted and observed values and it is obtained using;

$$MAE = \sum_{i=1}^{t} \frac{|Z_{obs} - Z_{pred}|}{t} \text{ ... ... (8)}$$

Root mean square error (RMSE)

It is the square root of the sum of square of the differences between the predicted values and the observed values dividing by their number of observation (t). It is given by:

$$RMSE = \sqrt{\frac{1}{t}\sum_{i=1}^{t}\left(Z_{obs} - Z_{pred}\right)^2} \text{ ... ... (9)}$$

When comparing models, the best one is the one with the least error whether MAE or RMSE.

Properties of a good ARIMA model

The following characteristics are considered in this research before the best among all competing models is selected.

(i) Stationary- It must have a relatively high stationary-R^2 value, usually in excess of 0.95

(ii) Invertible- Its MA coefficient must not be unreasonable high

(iii) Parsimonious- It must utilize small number of coefficient as possibly needed to explain the time series data

(iv) Its residuals must be statistically independent

(v) It must fit the time series data sufficiently well at the stage of estimation

(vi) Its MAE and RMSE must not be unnecessarily high

(vii) Sufficiently small forecast errors

Diagnostic checking

This is essential after the selection of a particular ARIMA model having estimated its parameters. The model's adequacy is verified by analyzing the residuals. The model is accepted if the residuals are found to be white noise, hence, the model selection procedure is restarted

The conformity of white noise residual of the model fit will be judge by plotting the ACF and the PACF of the residual to see whether it does not have any pattern or we perform Ljung Box Test on the residuals. The null hypothesis is:

H_0: There is no serial correlation

H_1: There is serial correlation

The test statistics of the Ljung box is;

$$LB = n(n+2)\sum_{i=1}^{n}\frac{\rho_k^2}{n-k} \quad \dots \chi_m \dots \dots (10)$$

Here, n is the sample size, m is the lag length and ρ is the sample autocorrelation coefficient.

The decision: if the LB is less than the critical value of X^2, then the null hypothesis is not rejected. This implies a small value of Ljung Box statistics will be in support of no serial correlation or i.e. the error term is normally distributed. This is concerned about the model accuracy.

Results and Discussions

The time plot shows that the exchange rate of Naira to dollar was relatively stable from 1960 to 1985 after when there was an obvious increase trend in the rate. A significant increment in the exchange rate was observed in the year 1998 to 1999 which kept on increasing till 2004 when a brief downward trend was observed till 2009. However, the rate jumped up significantly from 2009 to 2010 and the increment is sustained till 2015.

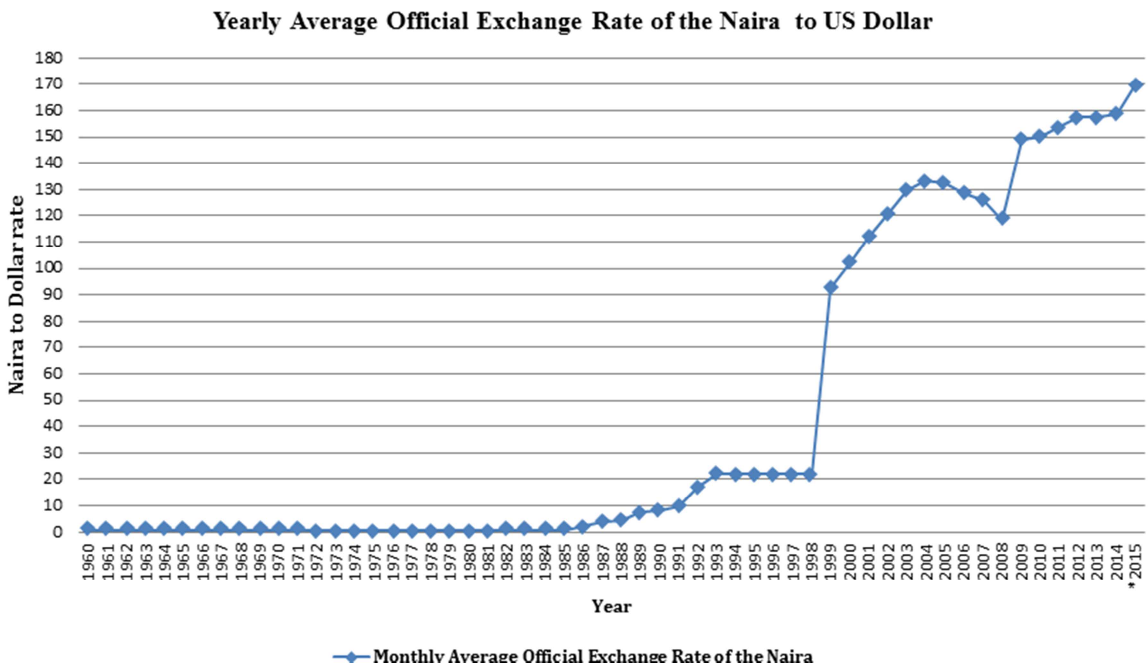

Chart 1: Time plot of yearly exchange rate of the naira to US dollar from 1960 - 2015

Autocorrelation function

Since the autocorrelation coefficient (Table 1) starts at a very high value at lag 1 (0.942) and declines rapidly as the lag lengthens, this indicates that exchange rate (Naira to Dollar) is a non-stationary series. This is supported by the auto-correlogram (Chart 2) that follows with most of the point falling outside the control limit and the point falling above the positive side of the chart (no randomness), hence the series is not stationary. This table shows various values obtained for autocorrelations of exchange rate of Nigeria naira to US dollar at the first 16 lags. The value of autocorrelation function for lag i, i = 1 to 16 is obtained using:

$$\rho_{X_t,X_{t-i}} = \frac{\sum_{t=1}^{n}(x_t-\bar{x}_t)(x_{t-i}-\bar{x}_{t-1})}{\sqrt{\sum_{t=1}^{n}(x_t-\bar{x}_t)^2\sum_{t=1}^{n}(x_t-\bar{x}_{t-1})^2}} \dots\dots\dots (11)$$

Table 1: ACF of exchange rate of naira to dollar

Lag	Autocorrelation	Std. Error	LB Statistic	
			Value	Sig.
1	.942	.130	52.413	.000
2	.887	.129	99.694	.000
3	.827	.128	141.635	.000
4	.764	.127	178.111	.000
5	.701	.125	209.390	.000
6	.638	.124	235.836	.000
7	.573	.123	257.580	.000
8	.524	.122	276.125	.000
9	.468	.120	291.293	.000
10	.412	.119	303.270	.000
11	.341	.118	311.658	.000
12	.267	.116	316.932	.000
13	.193	.115	319.751	.000
14	.122	.114	320.899	.000
15	.055	.112	321.140	.000
16	-.006	.111	321.144	.000

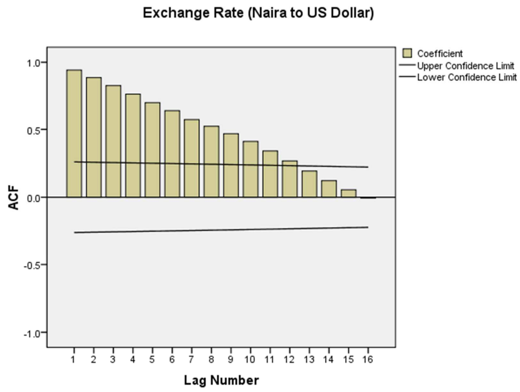

Chart 2: Auto-correlogram of the original exchange rate (naira to dollar) for 16 lags

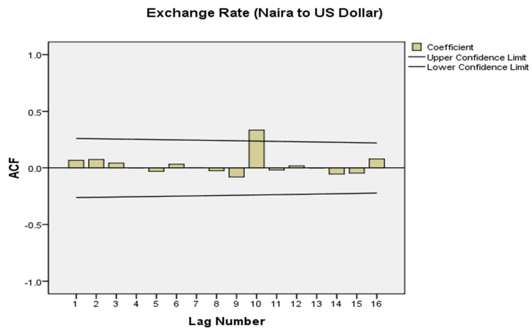

Chart 3: Auto-correlogram of the first differenced exchange rate (naira to dollar) for 16 lags

Table 2: ACF (First Differenced)

Lag	Autocorrelation	Std. Error	LB Statistic	
			Value	Sig.
1	.066	.131	.252	.615
2	.074	.130	.573	.751
3	.042	.129	.678	.878
4	.000	.128	.678	.954
5	-.031	.126	.736	.981
6	.032	.125	.801	.992
7	.002	.124	.801	.997
8	-.026	.122	.847	.999
9	-.081	.121	1.295	.998
10	.337	.120	9.196	.514
11	-.020	.118	9.223	.601
12	.017	.117	9.243	.682
13	-.001	.116	9.243	.754
14	-.055	.114	9.476	.799
15	-.047	.113	9.647	.841
16	.078	.112	10.132	.860

Table 3 and Chart 3 show that the series is stationary after the first difference since most of the points hover around zero and show randomness. This suggests that is will be essential to difference the original series at least once for predictive purpose. It can also be observed from the chat that almost all the points fall within the control limit.

When no transformation was made (Table 4a) there are disparities on the efficiency of various competing models ARIMA (2,0,2) has the best stationary-R^2; ARIMA (1,1,1) and ARIMA (2,1,2) have the best R^2; ARIMA (1,1,1) has the least RMSE; ARIMA (2,2,2) has the least MAE; while ARIMA (1,0,0) has the most desirable Ljung-Box Q statistics. However, when various competing models are considered across the board by rating their efficiency, ARIMA (1,0,0) and ARIMA (2,0,2) best explained the series with higher preference for the former since it has lower Normalized Bayesian Information Criteria (NBIC) of 5.044 and Ljung-Box Q Significant value of 0.956.

Table 3: Summary table of competing models

Transformation	Model Type	Statistics					LB Q(18)	
		Stationary R^2	R^2	RMSE	MAE	Normalized BIC	Statistics	Sig.
None	ARIMA (1,0,0)	0.968	0.968	11.179	6.020	5.044	8.444	0.956
	ARIMA (2,0,2)	0.971	0.971	10.948	4.816	5.218	10.659	0.713
Square Root	ARIMA (1,0,0)*	0.976	0.973	10.341	4.079	4.888	7.180	0.981
	ARIMA (1,0,1)	0.976	0.973	10.436	3.959	4.978	7.333	0.966
	ARIMA (2,0,0)	0.976	0.973	10.436	3.960	4.978	7.352	0.966
	ARIMA (2,0,1)	0.980	0.973	10.494	3.852	5.061	9.343	0.859
Natural Log	ARIMA (2,0,1)	0.988	0.970	11.145	4.493	5.181	11.482	0.718
	ARIMA (2,0,2)	0.985	0.968	11.511	4.613	5.318	7.449	0.916

Table 4a: ARIMA models with various statistics (No Transformation)

Model Type	Statistics					LB Q(18)	
	Stationary R^2	R^2	RMSE	MAE	Normalized BIC	Statistics	Sig.
ARIMA (0,0,0)	0.731	0.731	32.285	28.563	7.093	258.235	0.000
ARIMA (0,0,1)	0.889	0.889	20.927	17.489	6.298	163.327	0.000
ARIMA (0,1,0)	0.061	0.972	10.388	4.357	4.827	12.007	0.847
ARIMA (0,1,1)	0.061	0.972	10.487	4.335	4.919	12.059	0.797
ARIMA (1,0,0)*	0.968	0.968	11.179	6.020	5.044	8.444	0.956
ARIMA (1,0,1)	0.968	0.968	11.274	5.875	5.133	8.868	0.919
ARIMA (1,1,0)	0.061	0.972	10.487	4.334	4.919	12.061	0.796
ARIMA (1,1,1)	0.114	0.974	10.291	4.856	4.954	11.509	0.777
ARIMA (1,1,2)	0.074	0.973	10.621	4.147	5.090	11.989	0.680
ARIMA (1,2,0)	0.253	0.959	12.873	4.666	5.332	22.185	0.178
ARIMA (1,2,1)	0.471	0.971	10.937	3.961	5.080	12.195	0.730
ARIMA (1,2,2)	0.470	0.971	11.061	3.993	5.176	12.274	0.658
ARIMA (2,0,0)	0.968	0.968	11.313	5.830	5.140	8.799	0.921
ARIMA (2,0,1)	0.966	0.966	11.795	4.826	5.295	7.939	0.926
ARIMA (2,0,2)*	0.971	0.971	10.948	4.816	5.218	10.659	0.713
ARIMA (2,1,0)	0.062	0.972	10.588	4.306	5.011	12.050	0.741
ARIMA (2,1,1)	0.074	0.973	10.622	4.215	5.090	11.770	0.696
ARIMA (2,1,2)	0.109	0.974	10.524	4.085	5.144	10.033	0.760
ARIMA (2,2,0)	0.325	0.963	12.357	4.638	5.324	17.385	0.361
ARIMA (2,2,1)	0.471	0.971	11.053	3.913	5.175	12.092	0.672
ARIMA (2,2,2)	0.482	0.971	11.041	3.855	5.246	12.393	0.575

Table 4b: ARIMA models with various statistics (Square Root Transformation)

Model Type	Statistics					LB Q(18)	
	Stationary R^2	R^2	RMSE	MAE	Normalized BIC	Statistics	Sig.
ARIMA (0,0,0)	0.814	0.856	23.636	19.418	6.469	262.513	0.000
ARIMA (0,0,1)	0.922	0.933	16.307	10.809	5.799	156.960	0.000
ARIMA (0,1,0)	0.041	0.970	10.885	4.454	4.920	9.200	0.955
ARIMA (0,1,1)	0.041	0.970	10.980	4.409	5.011	9.311	0.930
ARIMA (1,0,0)*	0.976	0.973	10.341	4.079	4.888	7.180	0.981
ARIMA (1,0,1)*	0.976	0.973	10.436	3.959	4.978	7.333	0.966
ARIMA (1,1,0)	0.041	0.970	10.979	4.409	5.011	9.311	0.930
ARIMA (1,1,1)	0.041	0.970	11.088	4.418	5.103	9.309	0.900
ARIMA (1,1,2)	0.082	0.972	10.826	4.349	5.128	9.472	0.852
ARIMA (1,2,0)	0.241	0.943	15.177	5.994	5.661	19.974	0.276
ARIMA (1,2,1)	0.477	0.968	11.414	4.699	5.165	9.349	0.898
ARIMA (1,2,2)	0.483	0.969	11.390	4.567	5.235	9.110	0.872
ARIMA (2,0,0)*	0.976	0.973	10.436	3.960	4.978	7.352	0.966
ARIMA (2,0,1)*	0.980	0.973	10.494	3.852	5.061	9.343	0.859
ARIMA (2,0,2)	0.976	0.972	10.734	4.223	5.178	7.651	0.907
ARIMA (2,1,0)	0.041	0.970	11.088	4.418	5.103	9.310	0.900
ARIMA (2,1,1)	0.083	0.972	10.803	4.388	5.124	9.335	0.859
ARIMA (2,1,2)	0.088	0.972	10.809	4.168	5.198	9.486	0.799
ARIMA (2,2,0)	0.318	0.953	13.902	5.804	5.560	13.623	0.627
ARIMA (2,2,1)	0.477	0.968	11.522	4.705	5.258	9.440	0.853
ARIMA (2,2,2)	0.479	0.969	11.590	4.693	5.344	9.508	0.797

Table 4c: ARIMA models with various statistics (Natural Log Transformation)

Model Type	Statistics					LB Q(18)	
	Stationary R^2	R^2	RMSE	MAE	Normalized BIC	Statistics	Sig.
ARIMA (0,0,0)	0.873	0.470	45.279	21.098	7.769	294.520	0.000
ARIMA (0,0,1)	0.950	0.840	25.089	11.737	6.660	186.648	0.000
ARIMA (0,1,0)	0.018	0.936	15.865	8.093	5.674	17.779	0.470
ARIMA (0,1,1)	0.055	0.937	15.780	7.920	5.736	16.089	0.518
ARIMA (1,0,0)	0.988	0.962	12.225	5.332	5.223	17.576	0.416
ARIMA (1,0,1)	0.988	0.960	12.661	5.538	5.365	14.485	0.563
ARIMA (1,1,0)	0.059	0.938	15.647	7.868	5.719	16.404	0.495
ARIMA (1,1,1)	0.067	0.944	15.094	7.711	5.720	16.076	0.448
ARIMA (1,1,2)	0.069	0.942	15.468	7.816	5.842	15.735	0.400
ARIMA (1,2,0)	0.189	0.849	24.632	8.929	6.630	30.726	0.022
ARIMA (1,2,1)	0.421	0.949	14.386	6.994	5.628	16.026	0.451
ARIMA (1,2,2)	0.422	0.949	14.880	7.028	5.730	15.114	0.443
ARIMA (2,0,0)	0.988	0.960	12.705	5.322	5.371	14.343	0.573
ARIMA (2,0,1)*	0.988	0.970	11.145	4.493	5.181	11.482	0.718
ARIMA (2,0,2)*	0.985	0.968	11.511	4.613	5.318	7.449	0.916
ARIMA (2,1,0)	0.063	0.940	15.547	7.839	5.779	16.677	0.407
ARIMA (2,1,1)	0.073	0.945	15.107	7.197	5.795	16.552	0.346
ARIMA (2,1,2)	0.070	0.942	15.593	7.771	5.931	16.660	0.275
ARIMA (2,2,0)	0.275	0.889	20.347	8.254	6.321	22.225	0.136
ARIMA (2,2,1)	0.406	0.940	15.801	7.969	5.890	16.433	0.354
ARIMA (2,2,2)	0.407	0.941	15.877	7.865	5.973	15.784	0.327

From various results obtained when square root transformation (Table 4b) was used ARIMA (1,0,0); ARIMA(1,0,1); ARIMA (2,0,0) and ARIMA (2,0,1) are competing models with all having a relatively higher stationary-R^2 and R^2 when compared with those obtained when no transformation was made on the original series. The models are also having lower NBIC and Ljung-Box Q statistics in comparison with those obtained when original series was used. However, ARIMA (1,0,0) and ARIMA (2,0,1) give best explanation to the series among the competing models and they both performed better than those obtained when no transformation was made to the series.

Under natural log transformation, ARIMA (2,0,1) and ARIMA (2,0,2) outperformed all other models. Both have best stationary-R^2 in comparison with square root transformation and original series. Between the two however, ARIMA (2,0,1) relatively perform better than ARIMA (2,0,2).

Conclusions

For prediction purpose, ARIMA model offers a good technique because its strength is in the fact that it is a suitable method for any time series with any pattern of change and it does not require the researcher to choose the value of any parameter a priori. However, its requirement of a long time series is a limitation. Like so many other methods, it does not assure a perfect forecast but it performs relatively better compared to competing models when dealing with time series data.

With the result from several tentative ARIMA models entertained and under different transformations, it is obvious that there is no any parameter combination (under respective transformations) that generally stands out among the rest. With all aforementioned expected characteristics of a very good ARIMA model, which include among other; stationarity, parsimoniousness, “acceptable” RMSE, MAE, relatively small forecast error, least NBIC (Normalized Bayesian Information Criterion), the most suitable model that relatively perform very well in comparison with all other models is ARIMA(1,0,0) when square root transformation is utilized.

The model has stationary R^2 of 0.976; coefficient of determination (R^2) of 97.3%; NBIC of 4.888 and Ljung-Box Q P-value of 0.981. Hence, the recommended model for forecasting of average yearly exchange rate of Nigeria naira to US dollar. This research has provided empirical forecasts of the exchange rate in Nigeria. The exchange rate of Nigeria naira to US dollar is on the increasing side on the long run. ARIMA model has been shown to be more effective and efficient when data transformation is employed. A continuous depreciation of exchange rate of any country will make import more expensive. This in turns will negatively affect the entire economy across all the value chains. Therefore, countries must strive to reduce import and policies towards improving volume of export must be encouraged in order to have a favourable balance of trade occurs and hence a positive balance of payment. The policy implication of this research is for those involved in formulating foreign exchange policies to always compare various transformations of competing models before deciding on the final choice of the model to be adopted for prediction purpose.

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