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A COMPARATIVE STUDY OF BACK PROPAGATION ALGORITHM IN NEURAL NETWORK WITH BOX AND JENKINS APPROACH

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Abstract: **Artificial neural networks (ANN) have received a great deal of attention in many fields of engineering and science. Inspired by the study of brain architecture, ANNs represent a class of nonlinear models capable of learning from data. ANNs have been applied in many areas where statistical methods are traditionally employed. They have been used in pattern recognition, classification, prediction and process control. The purpose of this research is to compare ANNs and Box-Jenkins ARIMA time series models to forecast Naira/Dollars exchange rates. This research described an empirical study of modelling and forecasting time series data of Exchange rate of Nigeria Naira (N) to the USD ($). The Box-Jenkins ARIMA and Artificial Neural Network (ANN) methodologies were used for forecasting the monthly data collected from January 1991 to June 2018 through CBN website www.cbn.gov.ng. The diagnostic checking has shown that ARIMA (2, 1, 3) is appropriate. ANN with two time delay and one hidden neuron is also shown to be the best architecture trained for the data. However, the results Neural Networks trained by the Levenberg-Marquardt (LM) provides better forecasts than ARIMA model as it gives smaller mean square error.**

Keywords: **Artificial neural networks (ANN), Levenberg-Marquardt (LM), Box-Jenkins.**

1. INTRODUCTION

One of the largest and more volatile financial market is the foreign exchange market, exchange rates being among the most used and important economic indices. Forecasting the exchange rates is a difficult problem from both theoretical and practical point of view because the exchange rates are influenced by many factors like economic and political. Researchers' have been developed using different statistical and economic models for the purpose of forecasting exchange rates but still this problem remains one of the major challenges in the field of forecasting methods. An exchange rate which means the exchange one currency for another price for which the currency of a country (Nigeria) can be exchanged for another country's currency say (dollar) (Jhingan, 2003).Exchange rate is said to depreciate if the amount of domestic currency require purchasing a foreign currency increases, while the exchange rate appreciates if the amount of domestic currency require to obtain a foreign currency reduces. It determines there relative prices of domestic and foreign goods, as well as the strength of external sector participation in the international trade. A correct exchange rate does have important factors for the economic growth for most developed countries whereas a high volatility has been a major problem to economic of series of African countries like Nigeria. In Nigeria, exchange rate has changed within the time frame from regulated to deregulated regimes. Ewa(2011) agreed that the exchange rate of the naira was relatively stable between 1973 and 1979 during the oil boom era and when agricultural products accounted for more than 70% of the nation's gross domestic products (GDP) There are some factors which definitely affect or influences exchange rate like interest rate, inflation rate, trade balance, general state of economy, money supply and other similar macro – economic giants' variables.

Many researchers have been carried out in the literature to compare traditional time series models with computational models for forecasting. These models are unsatisfactory because they are parametric and some are based on the assumption that the time series been forecasted are linear and stationary. Many past studies (Binner *et al.***,** 2005; Hill *et al.*, 1996; Kohara *etal.*, 1997; Yao *et al.*, 1999; Giles *et al.,* 2001; Kaboudan, 2005; Tilakaratne *et al.*, 2007), suggest that non-linear models such as neural network models perform better than traditional time series linear models. Therefore, neural networks have been advocated as an alternative to traditional statistical forecasting methods.

"What is an artificial neural network?" is the first question that should be answered.

(Picton1994) answered this question by separating this question into two parts. The first part is why it is called as an artificial neural network. The reason of it can be explained that artificial neural network is a network of interconnected elements which are inspired from studies of biological nervous systems. In other words, artificial neural network is an attempt at creating machines that work in a similar way to the human brain by building these machines using components that behave like biological neurons. The second part is what an artificial neural network does. The function of an artificial neural network is to produce an output pattern using an input pattern cell (Mazunbar *et al.,* 2007), these features enable them to assess not designed instructions and generate the solution for them. Therefore, this method is considered as an effective and powerful approach for problem solving and analysis in several areas.

ANN plays a vital role in foreign exchange rate prediction process. It has flexible nonlinear function mapping capability, which can approximate any continuous measurable function with desired accuracy.ANN presents a number of advantages over conventional methods of analysis (Mazunbar*etal.* 2008), ANNs are universal and highly simple approximations first used in the fields of engineering and cognitive science. In recent years, ANNs have been increasingly popular in finance for tasks such as pattern recognition, classification, optimization, robotic control and time series estimation operations.

Artificial Neural Network (ANN) is more effective in describing the dynamics of non stationary time series due to its non parametric, noise tolerance, data driven and adaptive properties. Neural network models are different from traditional linear models and other parametric nonlinear approaches, which are often limited in scope when handling nonlinear or nonstandard problems. ANNs are universal function approximates that can map any nonlinear function without prior assumptions about the data.

By the development of ANN, researchers and investors are hoping that they can solve the mystery of exchange rate predictions. It has been shown that the ANN model, which is a type of non-linear model, is a strong alternative in the prediction of exchange rates. ANN is a very suitable method to find correct solutions especially in a situation which has complex, noisy, irrelevant or partial information.

2. BOX JENKINS ARIMA TIME SERIES APPROACH

The ARIMA is a statistical analysis model. It is mainly used in econometrics and statistics for time-series analysis. ARIMA model uses time series data to predict future points in the series. A non-seasonal ARIMA model is denoted by ARIMA (p, d, q), where p is the order of AR component, d is the difference and q is the order of MA component respectively.

$$\Phi_p(X) = 1 - \varphi_1 x - \ldots - \varphi_p x^p \qquad (1)$$

$$\Theta_q(X) = 1 + \theta_1 x + \ldots + \theta_q x^q \qquad (2)$$

The process $\{X_t\}$in (3.1) and (3.2) is an ARMA (p, q) process. If $\{X_t\}$ is a stationary and for each t the following relation holds

$$\Phi_p(B)X_t = \Theta_q(B)W_t \qquad (3)$$

Where B is the backward shift operator defined by $B^i X_t = X_{t-i}$ where $i = 1,2,\ldots$ and$\{W_t\}$ is white noise$\sim N(0,\sigma^2)$.

A time series $\{X_t\}$ is said to follow an integrated autoregressive moving averagemodel if the dth difference if $W_t = \nabla^d X_t$ is a stationary ARMA process. If $\{W_t\}$ follows an $ARMA(p,q)$ model we can say that $\{X_t\}$ is an $ARIMA(p,d,q)$ process. For practical purposes we take $d = 1$ or at most 2.

Consider an $ARIMA(p,1,q)$ process with $W_t = X_t - X_{t-1}$, we have that,

$$W_t = \phi_1 W_{t-1} - \phi_2 W_{t-2} + \ldots + \phi_p W_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \qquad (4)$$

we can also write (3.4) in terms of observed series

$$\begin{aligned} X_t - X_{t-1} = \phi_1(X_{t-1} - X_{t-2}) + \phi_2(X_{t-2} - X_{t-3}) + \ldots + \phi_p(X_{t-p} - X_{t-p-1}) \\ + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \end{aligned} \qquad (5)$$

from (3.5) we have

$$\begin{aligned} X_t = (1+\phi_1)X_{t-1} + (\phi_2 - \phi_1)X_{t-2} + (\phi_3 - \phi_2)X_{t-3} + \ldots + (\phi_p - \phi_{p-1})X_{t-p} - \phi_p X_{t-p-1} \\ + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \end{aligned} \qquad (6)$$

we call (3.6) the difference equation form of the model.

The general $ARIMA(p,d,q)$ model using the backshift can be expressed concisely as

$$\phi(B)(1-B)^d X_t = \theta(B) e_t \qquad (7)$$

where ϕ and θ are the autoregressive and moving average polynomials respectively, B is the backward shift operator and e_t is the white noise.

In order to estimate ARIMA model, we have to do 4 steps as follow: Recognizing model, estimating variables and choosing model, testing model and forecasting (Gujarati, 2014).

3. ARTIFICIAL NEURAL NETWORK APPROACH

Artificial neural networks are adaptive computational models inspired by the biological human brain system**.** Unlike other analytical tools, they have been capable of solving complex problems, such as function approximation, classification, and pattern recognition. Moreover, they have been used as optimization tools for complicated and non-linear problems. A typical ANN consists of multiple neurons organized in a layered fashion and connected to each other forming an inter-dependent network. Neurons are the basic building blocks of all neural networks. Figure 1 illustrates a simple neuron.

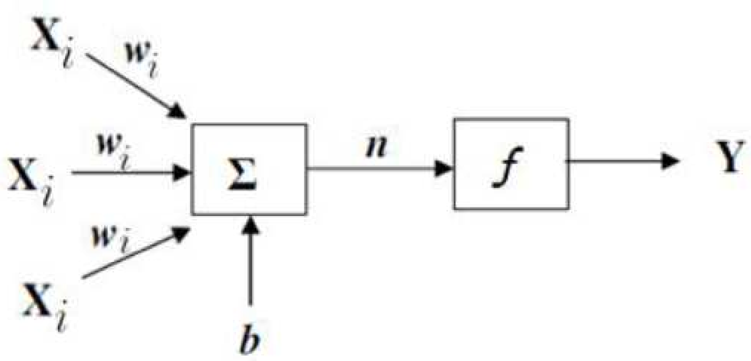

Figure 1: Basic Neuron.

A neuron can have one or more inputs and one or more outputs; the output of the neuron is the result of a non-linear combination of the inputs $\{X_i\}$, weighted by the synaptic weights $\{w_i\}$, and the application of a function $\{f\}$ on the result. Gupta et al. (2003) explain that each neuron has a relative weight that represents the importance of the signal it sends; these weights are assigned according to past experience gained through training. They add that after multiple weighted signals are combined in the neuron, further processing is conducted using a special function called the activation function $\{f\}$. The set of inputs to a neuron generally includes a bias $\{b\}$ whose value is constant and equal to 1.

An activation function, or sometimes called transfer function, is a function applied to the weighted sum of the inputs and the bias as shown in the following equation:

$$Y = f(wX + b) \tag{8}$$

The function can be of linear or non-linear nature, some of these functions include pure-linear, sigmoid, hyperbolic, and Gaussian. Figure 2 illustrates some of the commonly used functions.

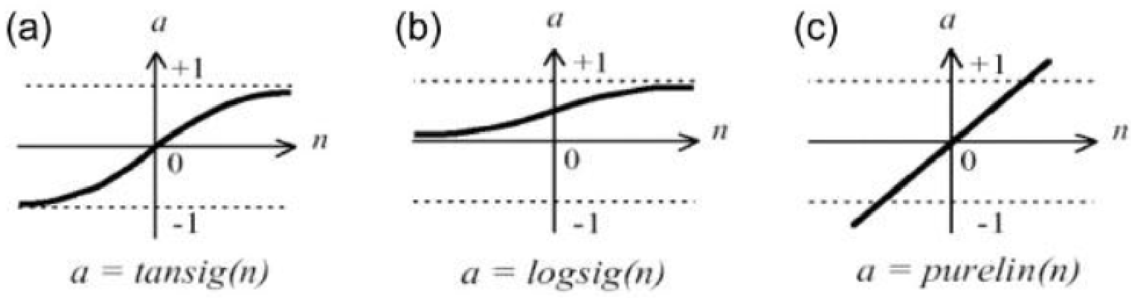

Figure 2: Examples of transfer functions

Neurons are the building blocks for any type of network and always work in the form discussed above. These neurons are arranged and connected in a layered fashion; because data passes sequentially from one layer to the other, the first layer is called an input layer and the last layer is called an output layer. There are two types of neural networks: feed-forward and recurrent (feedback) neural networks.

In this research, Nonlinear Autoregressive (NAR) Neural Network is a time lagged feed-forward networks type is used. The NN topology consists of l_x inputs, one hidden layer of H_0 neurons, and one output neuron as shown in figure.3 below. The learning rule used in the learning process is based on the Levenberg-Marquardt method (Bishop, 1995).

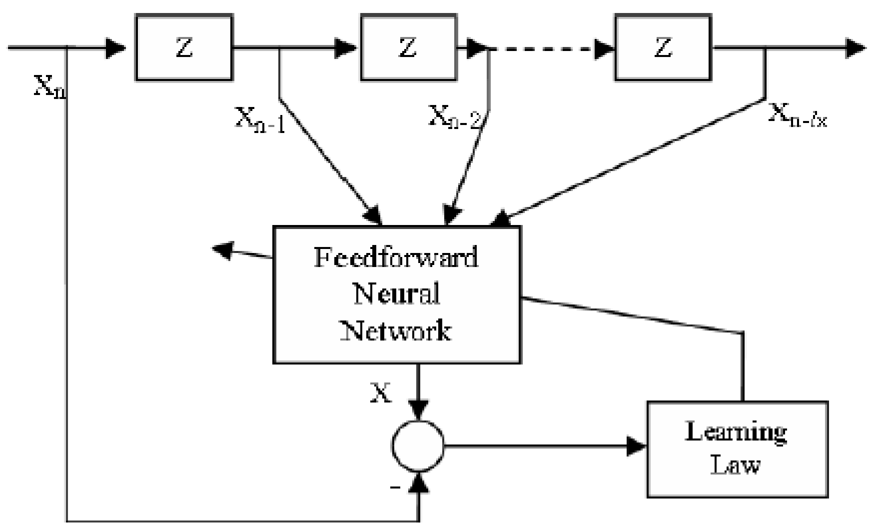

Figure 3: Neural Network-based nonlinear predictor filter. The one-step delay operator is denoted by Z

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4. RESULTS AND DISCUSSION

Figure 4 shows the plots of the Monthly records of the Naira/Dollar Exchange rate. Informally, the graph suggests that the prices of this variable are either trending or non-stationary. Therefore, this series requires transformation of one form or the other in order to stabilize their systems. After the first difference is taken, the graph as shown figure 5 informally suggests that the series is stationary as requires by the Box-Jenkins's methodology for forecasting. Augmented Dickey Fuller (ADF) unit root test was later used as formal test of stationarity. According to the results of table 1, H_0 which states that the series is non stationary is rejected after the first difference and therefore it is concluded that the series is stationary in its mean and variance which is also shown in figure 6. Thus, there is no need for further differencing the time series and we adopt d = 1 for our ARIMA (p,d,q) model.

We can clearly observe from table 2 that the lowest AIC and BIC values are for the ARIMA(2,1,3) model with (p=2, d=1 and q=3) and hence this model is considered to be the best predictive model for making forecasts for future values of our time series data. The final step of model fitting is model choice or model selection (Shumway, Stoffer, 2011).

The estimates of ARIMA (2,1,3) were summarized in table 3, the coefficients of the model were valid and stationary condition was met and satisfied since the coefficients are all less than one (-0.540507,-0.558381,-0.067657,-0.103529 and-0.828814) and all with the exception of $theta\_1$ are also significantsince their p – value are less than 0.1, 0.05 and 0.01.This means that the overall significance of the coefficients of ARIMA (2, 1, 3) was accepted and hence both AR (2) and MA (3) thus explain the series. The model adequacy was also confirmed in table 4 and figure 7.

The neural network proposed was trained using Levenberg Marquardt, a Variant of Backpropagation for weights and biases updates. An Intel (R) Core (TM) i3-2310M CPU @ 2.10GHz processor was used to train the proposed neural network models. A figure 8 is an example of the trained NAR configuration which is used for training purposes which are generally referred to as (Open loop). Similarly, a figure 9 otherwise known as closed loop is used for multi-step ahead prediction. In order to train, validate and test the neural networks developed using the LM algorithms, we have divided the data set in the following way: 70% of it for the training process, 15% for the validation process and the remaining 15% for the testing process. In all the cases, the samples have been randomly chosen as to cover the specified percentages. In order to train the neural networks, we have used the mean square error (MSE) as an objective function. Different NAR models were trained and their results summarized in table 5. The results revealed that ANN (2, 1) has least mean square error value of 29.12403. The two models of ARIMA (2, 1, 3) and ANN (2, 1) as best models forecasting Naira/Dollar exchange rate were then compared in forecasts by the figures 10 and 11 respectively.

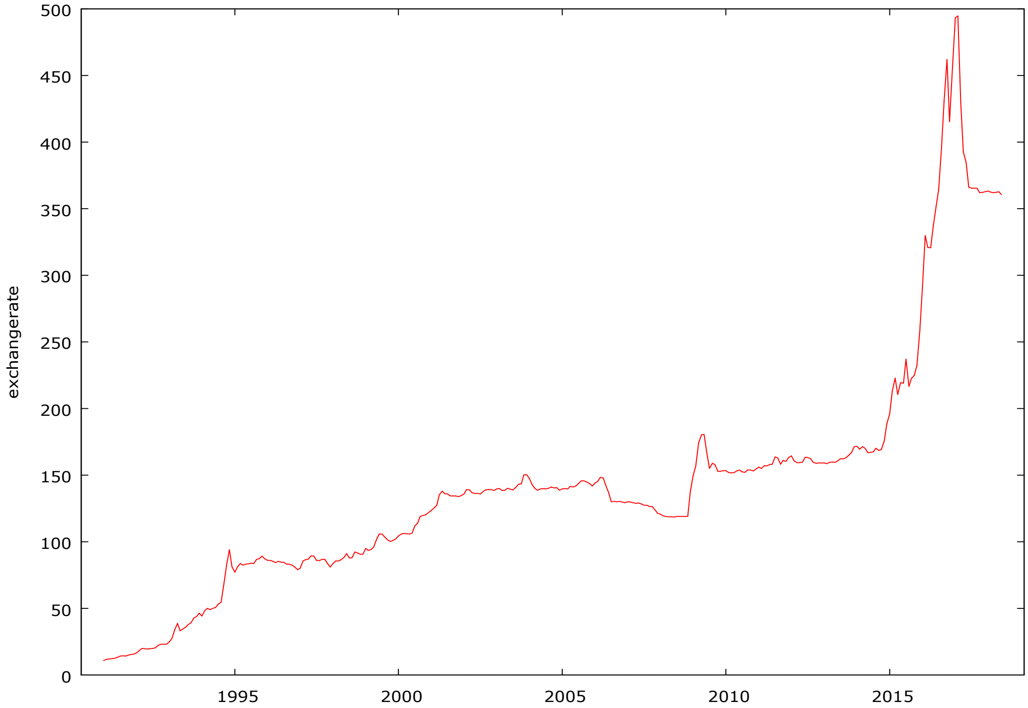

Figure 4: Time series plot of Monthly Naira/Dollar Exchange rate (1995-2018)

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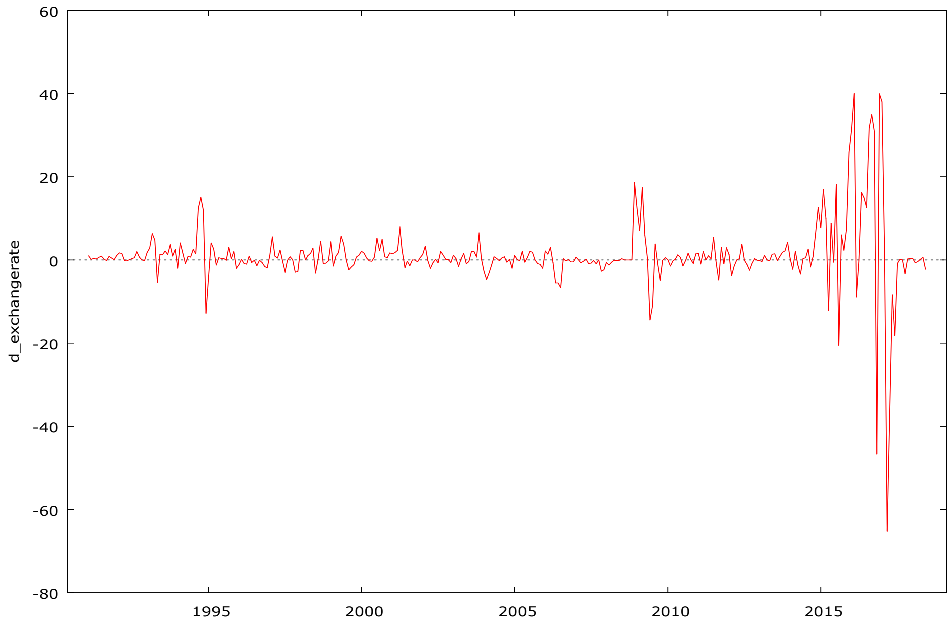

Figure 5: Time series plot of the first difference for Monthly Naira/Dollar Exchange rate

Table1: Augmented Dickey Fuller (ADF) unit root test

Level of the series	Type	P-value	Decision
Before differencing	Constant	0.9998	Not stationary
	Constant and trend	0.9995	Not stationary
	GLS	0.9996	Not stationary
After differencing	Constant	3.524e-010	Stationary
	Constant and trend	3.014e-009	Stationary
	GLS	1.016e-006	Stationary

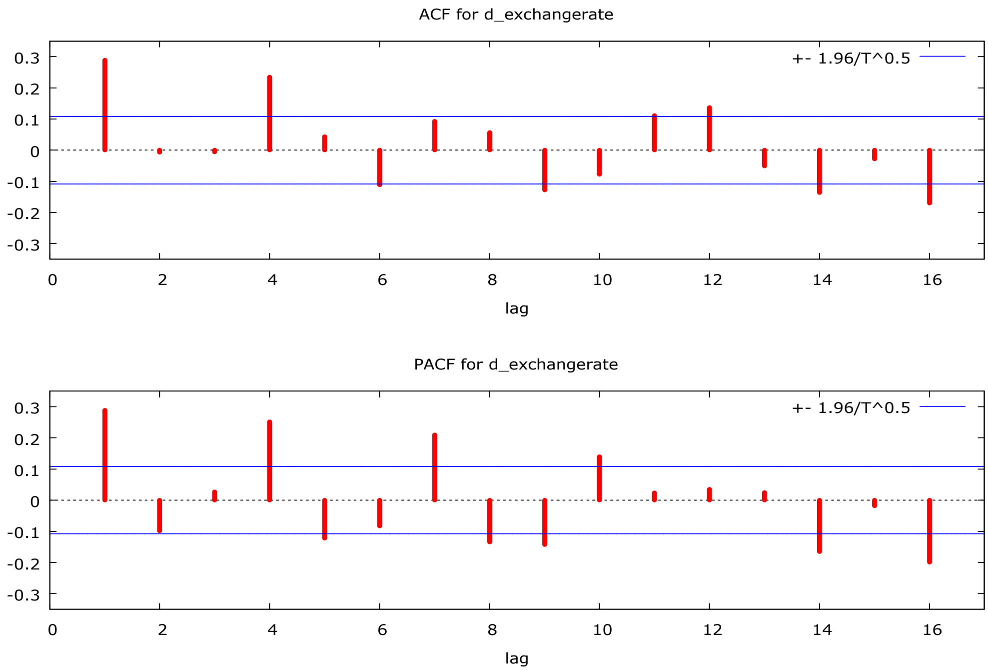

Figure 6: Exchange Rate Correlograms of the differenced series

Table 2: Comparison of Selected ARIMA Models

ARIMA MODELS	AIC	SIC	HQC
ARIMA(0,1,1)	2304.898	2323.863	2312.464
ARIMA(1,1,0)	2414.258	2425.637	2418.798
ARIMA(1,1,1)	2306.028	2321.200	2312.081
ARIMA(1,1,2)	2305.630	2324.595	2313.197
ARIMA(2,1,1)	2304.898	2323.863	2312.464
ARIMA(2,1,2)	2306.857	2329.615	2315.937
ARIMA(1,1,3)	2299.234	2312.992	2308.314
ARIMA(3,1,1)	2322.233	2344.991	2331.313
ARIMA(2,1,3)	**2267.192**	**2293.743**	**2277.785**
ARIMA(3,1,2)	2305.735	2332.286	2316.286
ARIMA(3,1,3)	2269.133	2299.477	2281.240

Table 3: ARIMA (2, 1, 3)

	Coefficient	Std. error	Z	P-value
Constant	0.00470678	0.00567147	0.8299	0.40659
Phi_1	-0.540507	0.0838054	-6.4495	<0.00001
Phi_2	-0.558381	0.0732404	-7.6240	<0.00001
$theta\_1$	-0.067657	0.061992	-1.0914	0.27510
$theta\_2$	-0.103529	0.0544518	-1.9013	0.05726
$theta\_3$	-0.828814	0.0550815	-15.0470	<0.00001

Table 4: ACF and PACF of residuals

LAG	ACF	PACF	Q-STAT	P-VALUE
1	-0.0080	-0.0080	0.0210	0.885
2	0.0441	0.0440	0.6653	0.717
3	0.0752	0.0760	2.5477	0.467
4	0.0934	0.0936	5.4615	0.243
5	0.0280	0.0244	5.7247	0.334
6	-0.0490	-0.0628	6.5319	0.366
7	0.0611	0.0435	7.7899	0.351
8	0.0019	-0.0045	7.7910	0.454
9	-0.0566	-0.0587	8.8777	0.449
10	-0.0550	-0.0564	9.9059	0.449
11	0.0359	0.0332	10.3448	0.500
12	0.1409	0.1550	17.1446	0.150
13	-0.0557	-0.0298	18.2105	0.144
14	-0.1286	-0.1481	23.9099	0.047
15	0.0465	0.0147	24.6586	0.055

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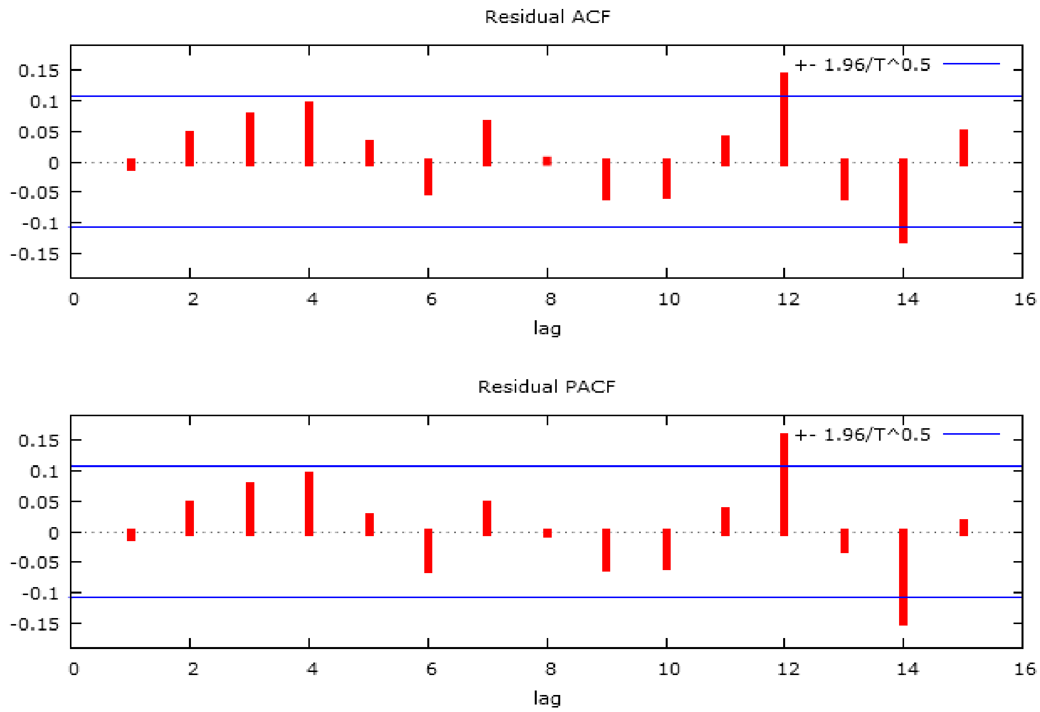

Figure 7 ACF and PACF of the residuals plots

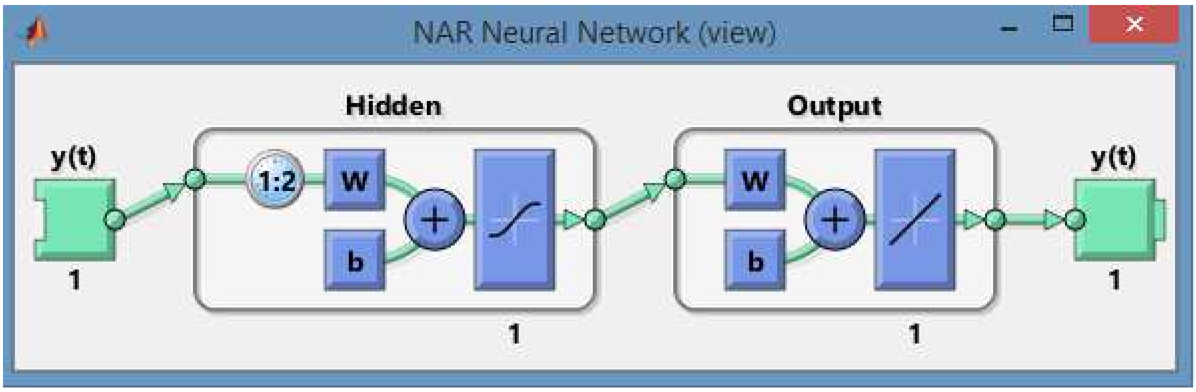

Figure 8: Open-Loop Hybrid Model I Architecture for Naira/Dollar Exchange Rate Forecaster

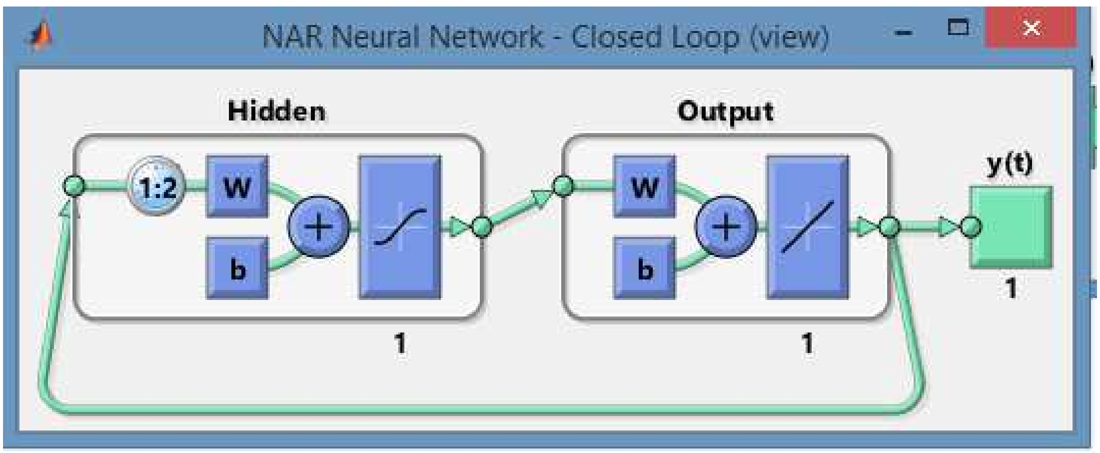

Figure 9: Closed-Loop Hybrid Model I Architecture for Naira/Dollar exchange Forecaster

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Table 5: Comparison of ANN Selected Models based on MSE

ANN(time delay, number of hidden layer)	Mean Square Error
ANN (1,1)	473.9119
ANN(1,2)	360.644
ANN(2,1)	**29.12403**
ANN(2,2)	154.5128
ANN(3,1)	117.932
ANN(3,2)	241.9134
ANN(4,1)	343.9683
ANN(4,2)	220.5765
ANN(5,1)	157.2427
ANN(5,2)	127.7597

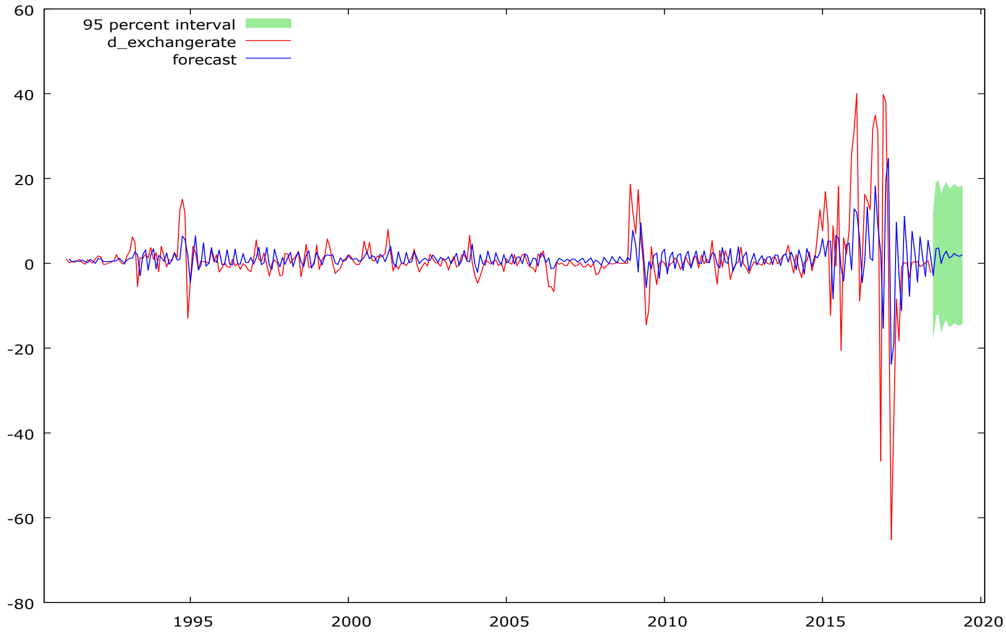

Figure 10: Response of Naira/Dollar exchange rates by ARIMA (2, 1, 3)

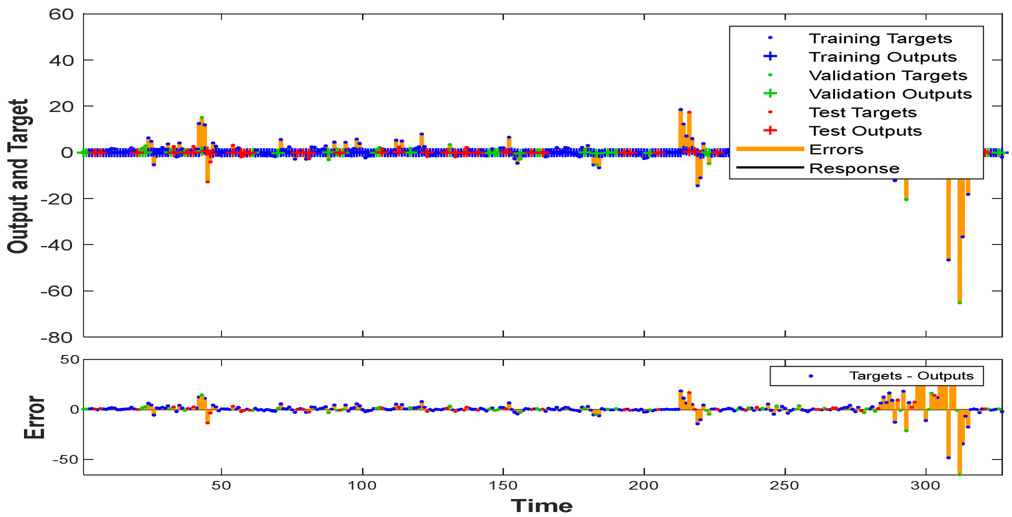

Figure 11: Response of Naira/Dollar exchange rates by ANN (2, 1)

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5. CONCLUSION

This paper is based on the application of traditional time series models. One of the limitations is that these models produce better results in relatively stable markets and could not capture violent markets. In this research, Naira/Dollar exchange rate was modelled using traditional time series based on Box and Jenkins approach and artificial neural network models. The results of the two models demonstrate that the artificial neural model provide better Naira/Dollar forecasts than the traditional time series model as it has the smaller minimum mean square error.

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