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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 modeling and forecasting time series data of Exchange rate of Nigeria Naira (N) to the USD ($). The Box-Jenkins seasonal ARIMA and Artificial Neural Network (ANN) methodologies were used for forecasting the monthly data collected from January 1991 to June 2018 through CBN website www.cbn.gov.ng. The diagnostic checking has shown that SARIMA (2, 1, 3) (0, 0, 1)$_{12}$ 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 SARIMA model as it gives smaller mean square error.

1. Introduction

Before the establishment of structural adjustment programme in Nigeria in 1986, there was a fixed exchange rate in the country which was maintained by the exchange control regulations that brought about significant distortions in the economy. This is because Nigeria depends seriously on imports from different countries as nearly all industries import their raw materials from foreign countries. Similarly, there were huge importation of finished goods with the adverse consequences for domestic production, balance of payments position and the nation's external reserves level [1].

Foreign exchange market is one of the largest and more volatile financial market, exchange rates being among the most used and important economic indices usually attracts attention of the research in both academia and professional careers. Forecasting the exchange rates is a difficult problem from both theoretical and practical point of view because the exchange rates are influenced by many economic and political factors. Researchers have developed 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 of one currency for another price for which the currency of a country (Nigeria) can be exchanged for another country's currency say (dollar) [2].

Traditionally, Autoregressive integrated moving average(ARIMA) models are considered as some of the most widely used linear models in time series forecasting because of their theoretical elaborateness and accuracy in short-term forecasting [3]. However, ARIMA models cannot easily capture non linear patterns resulting from the existence of a bounded rationality assumption in financial markets [4]. In recent years, however, interest in the use of artificialneural networks (ANNs) for forecasting and time series prediction has grown steadily[5,6, 7]. But application of the ANN to forecast financial and economic variables in Nigeria is very limited and so the aim of this paper is to compare the ability of ANN with the traditional autoregressive models in forecasting Naira/Dollar exchange rate in Nigeria. In this paperwe compare traditional time series ARIMA model with artificial neural networks. The comparability or superiority of the proposed models has been investigated using Naira/Dollar exchange rate. The main motivation of this approach is due to the existence of little empirical evidence regarding the performance of ANN and ARIMA models under different characteristics of financial time series.

Many researchers have conducted research on forecasting of exchange rate for developed and developing countries using different approaches. The approach might vary in either fundamental or technical approach. Recently, in Nigeria many researchers used Box Jenkins approach to forecast exchange rate between Naira and US Dollar [8, 9]. Similarly, such methods were also used to forecast exchange rate between Naira and other currencies in the world.

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For example, Naira/Euro exchange rate using SARIMA model was fitted in [10]. Volatility of Naira/Dollar exchange rate was estimated by [11, 12, 13] using traditional GARCH models. The application of ANN to modelling economic conditions is expanding rapidly [14- 17]. ANN and traditional smoothing techniques were used by [18] to forecast some macro economic variables including gross domestic product (volume, NGDPD), gross national savings (NGSD_NGDP), inflation (average consumer prices, PCPI), population (LP), total investment (NID_NGDP), unemployment rate (LUR), volume of exports of goods and services (TX_RPCH), volume of imports of goods and services (TM_RPCH) in Turkey. In their results, ANN has shown to outperform the traditional smoothing techniques in forecasting these variables.

2. Seasonal Auto Regressive Integrated Moving Average (SARIMA)

The ARMA is a general class of time series model. It is mainly used in econometrics and statistics for time-series analysis. ARMA models use time series data to predict future points in the series. A non-seasonal ARMA model is denoted by ARIMA (p, q), where p is the order of AR component, 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 (1) and (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 average model 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, where d is the difference

When both non-seasonal as well as seasonal factors are incorporated in a time series data then multiplicative seasonal ARIMA model may be used.

The SARIMA model can be expressed in the following ways

ARIMA (p, d, q) (P, D, Q) ^{S} .... (4)

Where

P = non-seasonal Autoregressive order
d = non-seasonal differencing
q = non-seasonal moving Average order
P = seasonal Autoregressive order
D = seasonal differencing
Q = seasonal moving Average order
S = time spend of repeating seasonal pattern

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.

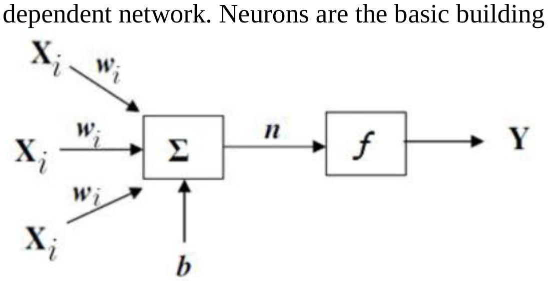

Figure 1: Basic Neuron.

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.

It was explained in [19] 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:

$$Y = f(wX + b) \qquad (5)$$

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.

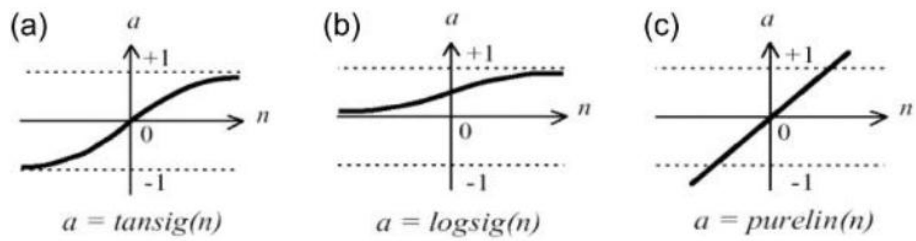

Figure 2: Examples of transfer functions
Neurons are the building blocks for any type of network and always work in the form discussed above. These neurons are arranged and connected in a layered fashion; because data passes sequentially from one layer to the other, the first layer is called an input 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 infigure 3 below. The learning rule used in the learning process is based on the Levenberg-Marquardt method [20].

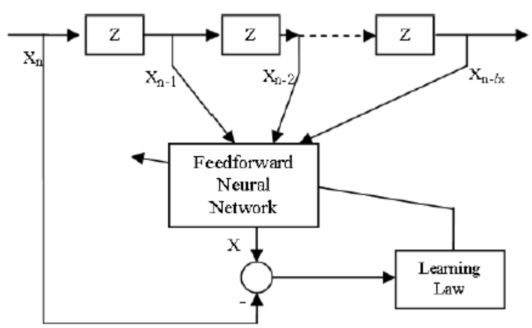

Figure 3: Neural Network-based nonlinear predictor filter. The one-step delay operator is denoted by Z

4. Results

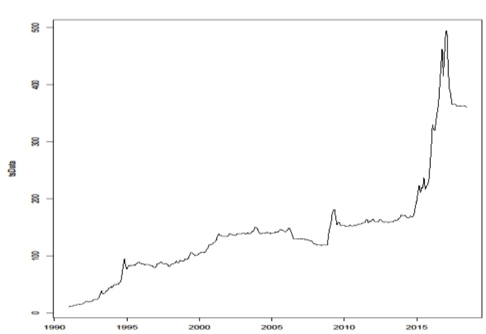

Figure 4: **Time series plot of Monthly Naira/Dollar Exchange rate (1991-2018)**

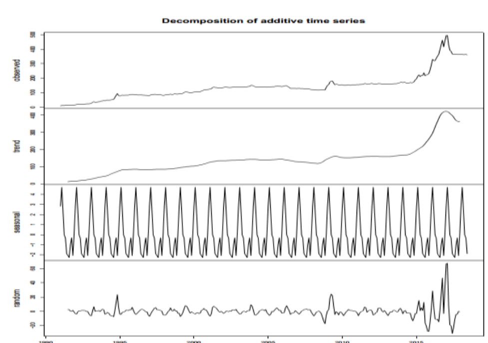

Figure 5: **Adjustment of time series seasonality**

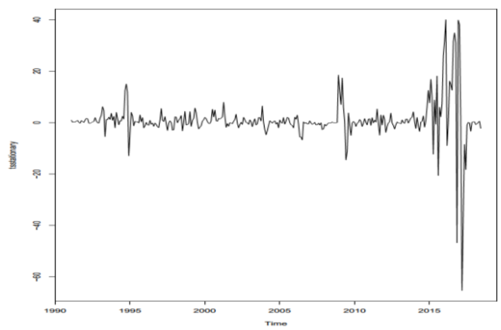

Figure 6: **Time series plot of the first difference for average Monthly Naira/Dollar Exchange rate (1991-2018)**

Table 1**: 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

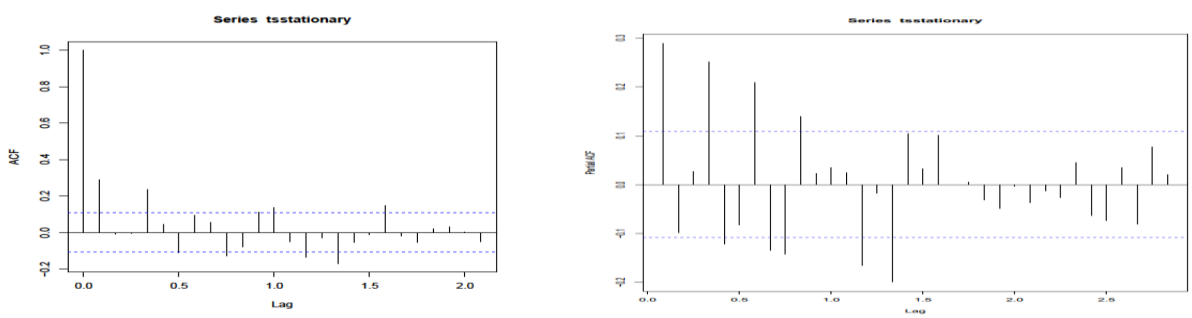

Figure 7: **Exchange Rate Correllogram of the differenced series**

Table 2: **Comparison of possible SARIMA Models**

ARIMA MODELS	AIC	BIC
SARIMA(2,1,2) $(1,0,1)_{12}$	2271.533	2284.632
SARIMA(1,1,0) $(1,0,0)_{12}$	2309.599	2317.832
SARIMA(2,1,2) $(0,0,1)_{12}$	2296.072	2299.211
SARIMA(2,1,2) $(0,0,2)_{12}$	2269.190	2280.317
SARIMA(2,1,2) $(1,0,0)_{12}$	2270.080	2290.550
SARIMA(2,1,1) $(0,0,1)_{12}$	2300.920	2345.790
SARIMA(1,1,2) $(0,0,1)_{12}$	2287.860	2298.786
SARIMA(2,1,3) $(0,0,1)_{12}$	**2259.396**	**2267.989**
SARIMA(3,1,2) $(0,0,1)_{12}$	2269.544	2284.601
SARIMA(1,1,3) $(0,0,1)_{12}$	2276.543	2299.011
SARIMA(3,1,1) $(0,0,1)_{12}$	2299.820	2299.990

Table 3:SARIMA (2, 1, 3) $(0, 0, 1)_{12}$

	Estimate	Std. error	Z	P-value
AR1	-0.617858	0.157590	-3.9207	0.059503
AR2	-0.605060	0.109231	-5.5392	0.001646
MA1	1.009745	0.157201	6.4233	0.056351
MA2	0.929547	0.181580	5.1192	0.079766
MA3	0.036151	0.099880	0.3619	0.717395
SMA1	0.176119	0.061383	2.8692	0.004115

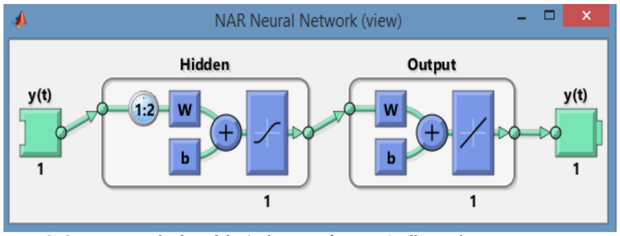

Figure 8: Open-Loop Hybrid Model I Architecture for Naira/Dollar Exchange Rate Forecaster

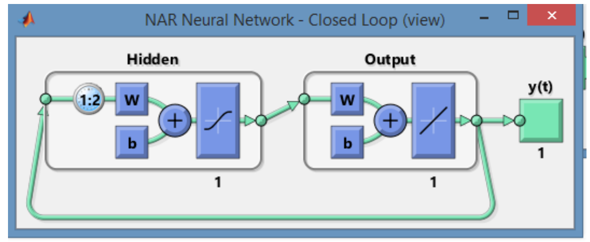

Figure 9: Closed-Loop Hybrid Model I Architecture for Naira/Dollar exchange Forecaster

Table 4: 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

Table 5: Forecast for seven months ahead

2018/2019	JUL	AUG	SEP	OCT	NOV	DEC	JAN
ANN	365.048	360.5096	366.8047	364.0477	365.5911	365.1593	358.2267
SARIMA	356.6950	336.0072	377.3829	357.5887	322.1324	393.0450	357.4850

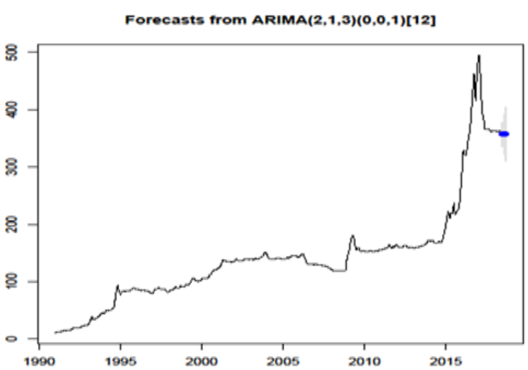

Figure 10: Response of Naira/Dollar exchange rates by SARIMA (2, 1, 3) (0, 0, 1)$_{12}$

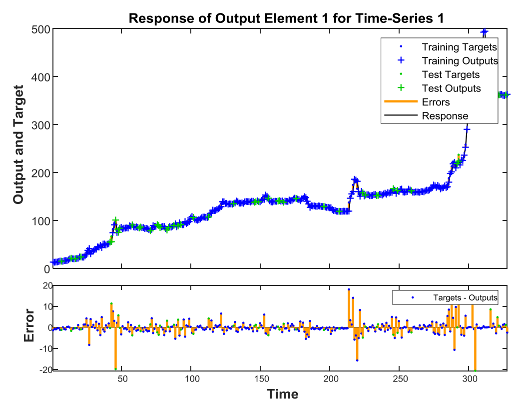

Figure 11: Response of Naira/Dollar exchange rates by ANN (2, 1)

Figure 4 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. The first transformation is shown in figure 5 where seasonality was removed from the data by subtracting the seasonal component from the original series and then difference it to make it stationary as shown in figure 6. Table 1 gives formal Augmented Dickey-Fuller (ADF) Test for the stationarity of the series under consideration. It tests null hypothesis (H_0) that the time series data is non-stationary. The results from the table shows that the data is not stationary before differencing and was found to be stationary immediately after taking the first difference

The sample ACF and PACF, shown in Figure 7, confirm the tendency of $\nabla(Yt)$ to behave as both having autoregressive and moving average processes as the ACF has significant peaks at different lags and the PACF is not tailing off. This would suggest the exchange rate data follows an ARIMA (p, d, q) process.

To select as the best suitable model for forecasting the series, two information selection criteria of BIC (Bayesian Information Criterion) and AIC (Akaike Information Criterion) were used as shown in table 2. It can clearly observe in the table above that the lowest AIC and BIC values are for the SARIMA(2,1,3) (0, 0, 1)$_{12}$ model with (p=2, d=1, q=3 and sma1) and hence this model can be the best predictive model for making forecasts for future values of our time series data.

The coefficients of SARIMA (2, 1, 3) $(0,0,1)_{12}$ model in table 3 were valid and stationary condition was met and satisfied since the estimates are all less than one (-0.67858, -0.605060, 0.929547, 0.036151, 0.176119) and all with the exception of MA(1) are also significant since their p – value are less than 0.1, 0.05 and 0.01.This means that the overall significance of SARIMA (2, 1, 3) $(0,0,1)_{12}$ was accepted and hence both AR (2), MA (3) and SMA(1) thus explain the series.
In this research, nonlinear autoregressive (NAR) neural network was used and 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.
Table 4 presents different architectural designs for the trained artificial neural network. The time delay which in time best known as lag order was varied from 1 to 5 with hidden neuron 1 and 2 in training these networks. However, the best performance is achieved by the ANN (2, 1); the architecture with two time delay in the input layer and one hidden neuron as it gives the least mean square error and hence selected as the model for forecasting Naira/Dollar exchange rate.
Table 5 presents the seven months ahead forecast for the Dollar/Naira exchange rate using two selected models ANN (2,1) and SARIMA (2,1,3) $(0,0,1)_{12}$ and observed that the trained artificial neural network tends to give better predicted values than the traditional SARIMA (2, 1, 3) $(0,0,1)_{12}$ time series model as it produces consistent value.
Similarly, figures 10 and 11 show in graphs the comparisons between the actual values and predicted values by the selected models.

5. Conclusion

This research consider a time series modelling of Naira/Dollar exchange rate using Box and Jenkins approach and artificial neural network models. The preliminary results of the time series Box and Jenkins model indicates that the series under consideration exhibits seasonal behaviour. It is however, found that the series is stationary after its first difference was taken.
The results of the two models further established that the artificial neural ANN (2,1) give more closer values Naira/Dollar forecasts than the traditional time series SARIMA (2,1,3) $(0,0,1)_{12}$ as it has the smaller minimum mean square error.

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