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A Hybrid Model for Forecasting Stock Market Indexes in Nigeria

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***Abstract* – In this study, the daily average stock price indexes for three banks in Nigeria was modeled and measured using three techniques. These techniques include the multiple linear regression (MLR) method, the cascade onward backtransmission neural network (CFBNN) method plus an amalgamation of a multiple linear regression method with cascade onward backtransmission neural network (MLR-CFBNN) method. The hybrid MLR-CFBNN was trained and tested on the increment series of the daily average stock price indexes of the three banks which are essentially univariate daily time sequence observations. An increment sequence of the original time sequence observations in this perspective refers to the difference series of the data. To determine the stationarity of the increment sequence, the Dickey-Fuller (DF) test was employed and the result revealed that the series is stationary. A comparison of the outcomes from the amalgamated MLR−CFBNN model and from the standalone cascade onward backtransmission neural network (CFBNN) technique as well as the standalone multiple linear regression (MLR) technique was conducted. Without loss of generality the developed hybrid MLR−CFBNN model displayed superior forecasting performance over standalone CFBNN and MLR techniques. This trend was achieved by the employment of the error of the mean in absolute terms commonly referred to as "mean absolute error" and the error root mean square (ERMS). The simulation was made possible by a MATLAB software compiler version 8.03. The developed hybrid model in this study is insightful and a prompt to the Securities and Exchange Commission to predict policies that will be in tandem with speculating the dynamics of stock businesses in Nigeria.**

***Keywords* – Hybrid, Regression, Neural Network, Forecasting, Stock Price Indexes, Time Series, JEL Classification: B22, C11, C15, C45.**

I. Introduction

Integrating predictions from diverse statistical and mathematical methods was pioneered by Bates and Granger [1] and ever since this combined method was founded, many authors have broadly applied the combining methodology in forecasting using statistical and mathematical models. The conjoining approach offers a superior substitute compared to employing a standalone model for forecasting Andrawis et al. [2].

Economic value series forecast has in recent times gathered momentous attention in the midst of practicing forecasters and stockholders as well as stockbrokers. Regression techniques and artificial neural network *(ANN)* are statistical techniques that have achieved tremendous growth in the analysis of stock market forces. Regression is the investigation of interactions amid variables, a major purpose of which is to forecast, or approximate the value of one variable from identified or presumed values of other variables associated to it. This study is centered on the analysis of the performance of a multiple linear regression (*MLR*) method, cascade forward backpropagation neural network (*CFBNN*) technique and a hybrid regression with a neural network technique. Here, we proposed a hybrid *MLR-CFBNN* method and compare its performance with standalone *MLR* method as well as standalone *CFBNN* method. The comparison of the respective performances of the foregoing techniques is made possible by two different measurements of error: root mean square error (*RMSE*) and mean absolute error (*MAE*). Also, in this study, we employed the daily stock market financial indexes of the Nigerian Stock Exchange (*NSE*) to simulate the hybrid *MLR-CFBNN* method as well as the standalone *MLR* and standalone *CFBNN* respectively. The simulation is made possible with *MATLAB* software, version 8.03.

The rest of this study is structured as follows. In Section 2, we present a literature review of the study in terms of its theoretical and empirical framework. In section 3, we present the methodology of the study with respect to conjoining of a multiple linear regression (*MLR*) model with a cascade forward backpropagation neural network (*CFBNN*) method, to form the proposed hybrid *MLR-CFBNN* technique for forecasting stock market indexes in Nigeria using the Bayesian model averaging *(BMA)* technique. In Section 4, we present results and discussions in the perspective of comparing forecasting performance of the hybrid *MLR-CFBNN* method with standalone multiple linear regression (*MLR*) method and standalone cascade forward backpropagation neural network (*CFBNN*) method using the root mean square error (*RMSE*) and mean absolute error (*MAE*). In Section 5, we present the conclusion and direction for upcoming studies in forecasting.

II. Literature Review

A. *Theoretical Literature*

Carmichael [3] affirms a case where artificial neural network can be seen to contain several amount of knobs connected via loops. Every loop contains a specific numerical load associated by the load. Carmichael further emphasizes that weights in neural network methods contains the strategic channels of lasting loading happening in the artificial neural network, such that a procedure of bringing up to date the loads called "learning" occurs at this point in the network. Lippmann [4] is of the view that a significant neural network method remains the residual backpropagation neural network scheme and it is a multi-layer feed forward neural network. He stresses that the backpropagation neural network scheme is suitable, merely once the scheme of the network is in use applicably.

The residual backpropagation system is able to train the backpropagation neural network image solidity but its drawback is that it converges very slowly. Frequently, forecasting and modeling progresses in a recurrent pattern and there exist no 'logical direction' in the widest sense. Also, one may model to obtain forecasting outcomes, which allow enhanced control, but repetition is again expected to be present and occasionally, there exist distinct methods to regulate difficulties. Neural networks can provide models for a large class of natural and artificial phenomena that are difficult to handle, using classical parametric techniques Enke and Thawornwong [5]. Neurons that are interconnected, such that, the neurons ploy in an analogous pattern with collective links, by means of weights are essential characteristics of artificial neural networks as asserted by Ibrahim et al. [6]. Different schemes in artificial neural network are applicable in diverse areas of statistics which includes: signal processing, image processing as well as pattern classification, as averred by Ibrahim et al. [6].

Generally, stock values can be perceived as a random time structure characterized by noise, and quite an amount of forecasting techniques have employed artificial neural networks to forecast stock price drifts Chenoweth and Obradovic [7]. Artificial neural networks possess good self-learning capability, a robust anti ramming proficiency, and have been extensively employed in economic processes such as exchange rate, profits, stock prices and risk analysis as well as prediction Pino et al. [8]. Stock market financial data is essentially a time series data since stock market prices are usually fashioned over a systematic selection of a specified process through time. Time series of stock market financial data are typically noisy and non-stationary. It is regarded as one of the sensational practices of forecasting of stock market financial series. Lu et al. [9] employed a two-stage modeling methodology involving support vector regression (*SVR*) and independent component analysis (*ICA*) to lessen the impact of noise in stock market financial time series forecasting. Furthermore, Lu and his friends assert that *ICA* is a new statistical signal dispensation method that was first developed to determine the fundamental source signals from detected mixture signals without having any previous knowledge of the mixing scheme. Their proposed method first uses *ICA* to the predicting variables for producing the independent components (*ICs*). After detecting and eliminating the *ICs* comprising the noise, the remaining *ICs* are then employed to reorganize the forecasting variables which have less noise and functioned as the input variables of the *SVR* forecasting model. In order to evaluate the performance of their developed technique, the *NIKKEI*225 opening index (which is the price weighted average of 225 stocks of the first section of the Tokyo Stock Exchange) and Taiwan Capitalization Weighted Stock Index (*TAIEX)* closing index are adopted as demonstrative instances. Experimental consequences publicized that the proposed approach outperforms the *SVR* technique with a random walk model and forecasting variables that are non-filtered.

B. *Empirical Framework*

Lu [10] beheld that the support vector regression (*SVR*) method is a new forecasting technique and has been excellently employed to clarify stock market financial series complications. Pai et al. [11] also developed a seasonal support vector regression (*SSVR*) model to predict seasonal stock market financial series observations. Seasonal factors and trends are employed in the *SSVR* model to make forecasts. Also, hybrid genetic algorithms and tabu search (*GA/TS*) algorithms were engaged in their work in order to pick three parameters of *SSVR* models.

Kisi and Guven [12] reports on studies of the capabilities of three distinct *ANN* techniques as black box models. They include radial basis neural networks (*RBNN*), generalized regression neural networks (*GRNN*) and multi-layer perceptron (*MLP*). They employed these black box models to approximate every day pan desertion. A comparison between the estimates of the *MLP*, the estimates of the *RBNN* as well as the estimates of *GRNN* techniques was executed. Also, the technique of Stephens-Stewart (*SS*) was also involved in the comparison. They employed the coefficient of determination statistics *R*2, root mean square errors (*RMSE*) and mean absolute error (*MAE*) to appraise the performances of the black box models. However, they found that the *MLP* and *RBNN* black box computing techniques might be used effectively to model the desertion process when the accessible climatic information is employed. They also found that the forecasting performance of the *GRNN* is greater than the *SS* method.

In a study presented by Okkan and Ali Serbes [13], where they proposed different hybrid methods for reservoir inflow modeling from meteorological data (monthly precipitation, one-month-ahead precipitation and monthly mean temperature data) by the joint application of discrete wavelet transform (*DWT*) and diverse black box modeling techniques. The black box modeling approaches considered in their study include: feed forward neural networks (*FFNN*), multiple linear regression (*MLR*) and least square support vector machines (*LSSVM*).

Rajurkar et al. [14] presented a combined or hybrid method which they termed "coupling between the linear model and the *ANN*". Their hybrid model combines the feed forward neural network (*FFNN*) technique which constitute the nonlinear artificial neural network (*ANN*) model and the least squares regression (*LSR*) technique which constitute the linear model in modeling and forecasting time series observations of daily rainfall-runoff. The input variable for the *FFNN* model emerged from the residual vector of the least squares regression (*LSR*) technique. The forecast outcomes obtained from the hybrid method indicated that they were reasonable.

Tseng et al. [15] presented a hybrid technique which coupled the feed-forward neural network back propagation (*FFNN*) technique and the seasonal autoregressive integrated moving average (*SARIMA*) technique. The forecasts and residual vector produced by the *SARIMA* technique served as input variables to the feed forward neural networks for the hybrid technique. The forecasting performance of the hybrid model revealed that it outperforms the forecasting performance of either the standalone feed forward neural network.

III. Data and Methodology

A. *Data*

In this study, we obtained the daily stock market indexes data from the Plateau State Investment and Property Company *(PIPC)* which is an affiliate of the Nigeria Stock Exchange *(NSE).* The data consist of the opening price and closing price of a stock for a period of about 16 years (4th March, 2005 to 4th January, 2020). However, we obtained the average score between the opening and closing price of a stock for the period stated above which we employed for the analysis. The data is essentially a time series data since it was recorded on daily basis. However, instead of using the opening price of a stock and/or the closing price of the stock, we determine the average value between the opening price of a stock and the closing price, which we employed for the simulation analysis. The average stock prices are for First Bank *Plc*, Guaranty Trust Bank *Plc* and Zenith Bank *Plc.* The total number of the average stock market indexes used in this study amounted to 3656 observations for each of the banks.

B. *Model Specification: The Multiple Linear Regression (MLR) Technique*

The construction of the proposed hybrid *MLR-CFBNN* method is explain in this section. Here, we demonstrate the integration of a multiple linear regression (*MLR*) model with a cascade forward backpropagation neural network (*CFBNN*) method, to form the hybrid *MLR-CFBNN* forecasting technique. The conjoining of the regression model and the neural network model is made possible by the Bayesian model averaging (*BMA*) technique which is a multi-model combination method.

Regression is the study of dependence. It is employed to response enquiries such as: Do modifications in diet result in variations in cholesterol level, and if so, do the results depend on additional features such as age, sex, and amount of physical exercise? Do nations with greater per person income have lower birth rates than nations with lower income? Regression analysis is a crucial measure of numerous research ventures Weisberg [16].

In this study, we employed the multiple linear regression equation of the form of equation (1) which measures the regression relationship among more than two variables. In equation (1), Y is the random.

$$\mu_Y / x_1, x_2, ..., x_k = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k \quad (1)$$

variable whose values we want to predict in terms of given values of $x_1, x_2, ..., x_k$, and $\beta_0, \beta_1, \beta_2, ...,$ and β_k.

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The multiple regression coefficients, are numerical constants that must be determined from observed data. For n data points $\{(x_{i1}, x_{i2}, \dots, x_{ik}, y_i); i = 1,2,\dots, n\}$ the least squares estimates of the $\beta's$ are the values $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \dots,$ and $\hat{\beta}_k$ for which the quantity in equation (2)

$$q = \sum_{i=1}^{n} \left[y_i - \left(\hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \dots + \hat{\beta}_k x_{ik} \right) \right]^2 \tag{2}$$

is a minimum. In this notation, x_{i1} is the ith value of the variable x_1, x_{i2} is ith value of x_2, and so on. So, we differentiate partially with respect to the $\hat{\beta}'s$, and equating these partial derivatives to zero, we presented these equations as equation (3).

$$\left.\begin{aligned}
\frac{\partial q}{\partial \hat{\beta}_0} &= \sum_{i=1}^{n} (-2) \left[y_i - \left(\hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_{i2} + \dots + \hat{\beta}_k x_{ik} \right) \right] = 0 \\
\frac{\partial q}{\partial \hat{\beta}_1} &= \sum_{i=1}^{n} (-2) x_{i1} \left[y_i - \left(\hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_{i2} + \dots + \hat{\beta}_k x_{ik} \right) \right] = 0 \\
\frac{\partial q}{\partial \hat{\beta}_2} &= \sum_{i=1}^{n} (-2) x_{i2} \left[y_i - \left(\hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_{i2} + \dots + \hat{\beta}_k x_{ik} \right) \right] = 0 \\
&\vdots \\
\frac{\partial q}{\partial \hat{\beta}_k} &= \sum_{i=1}^{n} (-2) x_{ik} \left[y_i - \left(\hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_{i2} + \dots + \hat{\beta}_k x_{ik} \right) \right] = 0
\end{aligned}\right\} \tag{3}$$

and finally $k + 1$ normal equations are presented as equation (4). In equation (4), we abbreviated our notation by writing $\sum_{i=1}^{n} x_{i1}$ as $\sum x_1, \sum_{i=1}^{n} x_{i1} x_{i2}$ as $\sum x_1 x_2$ and so on. These are extracts from Miller et al. [17].

$$\left.\begin{aligned}
\sum y &= \hat{\beta}_0 \cdot n + \hat{\beta}_1 \cdot \sum x_1 + \hat{\beta}_2 \cdot \sum x_2 + \dots + \hat{\beta}_k \cdot \sum x_k \\
\sum x_1 y &= \hat{\beta}_0 \cdot \sum x_1 + \hat{\beta}_1 \cdot \sum x_1^2 + \hat{\beta}_2 \cdot \sum x_1 x_2 + \dots + \hat{\beta}_k \cdot \sum x_1 x_k \\
\sum x_2 y &= \hat{\beta}_0 \cdot \sum x_2 + \hat{\beta}_1 \cdot \sum x_2 x_1 + \hat{\beta}_2 \cdot \sum x_2^2 + \dots + \hat{\beta}_k \cdot \sum x_2 x_k \\
&\vdots \\
\sum x_k y &= \hat{\beta}_0 \cdot \sum x_k + \hat{\beta}_1 \cdot \sum x_k x_1 + \hat{\beta}_2 \cdot \sum x_k x_2 + \dots + \hat{\beta}_k \cdot \sum x_k^2
\end{aligned}\right\} \tag{4}$$

C. *Model Specification: Cascade Forward Backpropagation Neural Network (CFBNN) Technique*

Thatoi et al. [18] declared the cascade forward backpropagation neural network (*CFBNN*) technique to be similar to the feed forward backpropagation (*FFBP*) neural network. The variation existing between them is such that in a feed forward backpropagation (*FFBP*) neural network, networks can perhaps be trained effectively in every input output relationship, in such a pattern that feed forward neural network (*FFNN)* with more layers might learn diverse associations. However, in the cascade forward backpropagation neural network (*CFBNN*) technique, the input variables are calculated after every hidden layer are back-propagated to the input layer and the weights attuned sequentially. The input variables are unswervingly connected to the finishing output and connection transpires amid the values obtained from the hidden layers and the values obtained from the input layers as well as weights are attuned accordingly. A study conducted by Sahoo et al. [19] on

International Journal of Innovation in Science and Mathematics
Volume 11, Issue 4, ISSN (Online): 2347–9051

approximating split size and spot in a steel plate by means of ultrasonic indicators and *CFBNN* neural networks, declared that the results obtained from *CFBNN* networks are better in performance than the *FFBP* networks. Figure 1, illustrates the *CFBNN* architecture where the inputs are linked to the hidden layer and the output layer. The architectural design of the neural network is frequently focus on the representative decision on data. The main architectural design is handled by the number of hidden layers and units. The cascade neural network output's neuron is linked to all parts by weights $w_1, w_2, \ldots, w_m$ which are modifiable during training. The standard sigmoid function f represents the output y of neurons in the network and is given by equation (5) that follows:

$$y = f(x, w) = \frac{1}{\left(1 + \exp\left(-w_0 - \sum_{i=1}^{m} w_i x_i\right)\right)} \quad (5)$$

where $X = (x_1, \ldots, x_m)$ is a $m \times 1$ input vector, $W = (w_1, \ldots, w_m)$ is a $m \times 1$ weight vector and w_0 is the bias term.

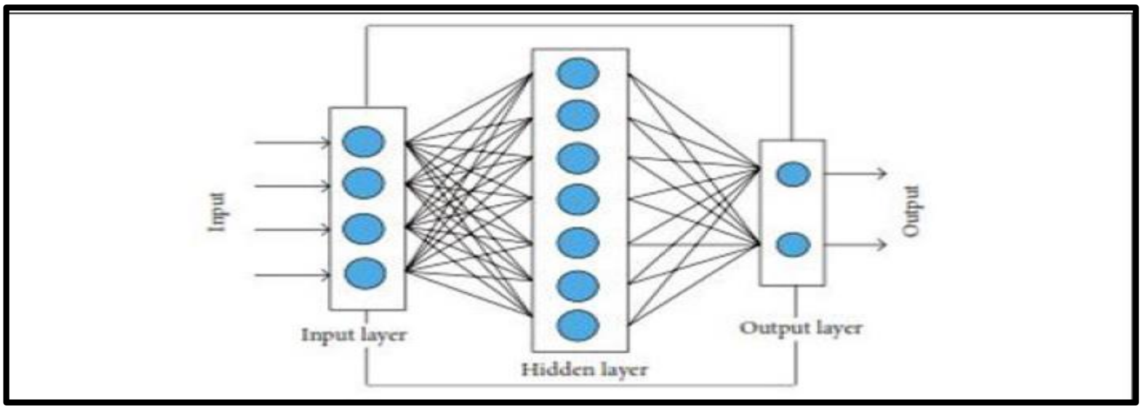

Fig. 1. Structure of Cascade Forward Backpropagation Neural Network Architecture.

D. *The Bayesian Model Averaging (BMA) Technique*

Saigal and Mehrotra [20] affirmed that a combination technique that merges the forecasts of two or more forecasting models is known as the Bayesian model averaging (*BMA*) technique. He declared that the *BMA* amalgamation technique generates a consensus weighted forecast on the basis of weighting the variances of any distinct model or weighting the prediction mean square errors of any lone model. In order to maintain the (*BMA*) technique employed in this study, we may advance as tag along. Suppose that $\varpi = \{\varpi_1, \varpi_2\}$ signifies a class with dual schemes which is measured in this article such that Ω represents some measure of engrossment referred to as the target input or variable, then the latter classification known as the posterior distribution of Ω given Ψ is presented in equation (6).

$$\rho_a(\Omega \mid \Psi) = \rho_a(\Omega \mid \omega_1, \Psi)\rho_1(\omega_1 \mid \Psi) + \rho_a(\Omega \mid \omega_2, \Psi)\rho_2(\omega_2 \mid \Psi) \quad (6)$$

Equation (6) is the mean of the posterior distributions in every classical model loaded with its consequential model weighted by the resultant posterior classical model stochastic measures. The foregoing process is named the Bayesian Model Averaging technique. Referring to equation (6), one would observed that the posterior likelihood of model ω_j such that $j = 1,2$ is specified as:

$$\rho_a(\omega_j \mid \Psi) = \frac{\rho_a(\Psi \mid \omega_j)\rho_a(\omega_j)}{\sum_{j=1}^{j=2}\rho_a(\Psi \mid \omega_j)\rho_a(\omega_j)} \tag{7}$$

such that $\rho_a(\Psi/\omega_j)$ is defined in equation (8).

$$\rho_a(\Psi \mid \omega_j) = \int \rho_a(\Psi \mid \zeta_j, \omega_j)\rho_a(\xi_j \mid \omega_j)d\xi_j \tag{8}$$

Equation (8) is the original probability of the classical model ω_j, ξ_j which is the trajectory of strictures of model ω_j and $\rho_a(\xi_j/\omega_j)$ is the previous solidity of ξ_j underneath the auspices of m ω_j, $\rho_a(\Psi/\xi_j, \omega_j)$ is the classical probability, and $\rho_a(\omega_j)$ is the previous likelihood that ω_j is the exact classical model. Entire likelihoods are totally restricted on ω_j the class of dual models that are entertained in this article wherever it is identical to the class of every probable combination of independent variables. The weights ϖ_j, j = 1, 2 is defined by $\varpi_j = \rho(\Psi/\omega_j)$ such that $\sum \varpi_j = 1$. There exist some striking characteristics of the *BMA* method. The *BMA* technique is predictively and statistically strong, such that it became the reason for which it is employed here as a nonlinear scheme in the modeling and forecasting approach. Also, the *BMA* technique allocates high weights to models that are superior in performance established on the chances of presenting a model. The *BMA* technique possesses a numerical variation which is less than the variances of some lone models since it handles effectively any inter-model-variance and intra-model-variance.

E. *Forecast Performance Evaluation*

An estimate of the typical amount of variation as declared by Chai and Draxler [21] is the error root average square, often referred to as "root mean square error". It refers to a disparity among forecast and the resultant empirical observations in which the sample is averaged and squared. Before averaging the errors, we squared the errors and then take the root of the mean of the errors, such that the root mean square error presents a reasonably lofty weight to huge errors. This implies that the error root mean square is mainly functional as soon as huge errors are predominantly unwanted. The error root mean square is expressed by equation (9) below.

Error root mean square (*ERMS*) = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i - P_i)^2}$ (9)

where M_i represents the actual amount produced, while P_i represents the predicted amount, while n represents the sample size in the class of figures. In another development, by Chai and Draxler [21] is the error of the mean in absolute terms as an estimate with complete amount of disparity amid the predictable observation with the original observation simultaneously such that the negative observations do not cancel the positive observations. The error of the mean in absolute terms is commonly referred to as "mean absolute error" and is often abbreviated by the acronym "*MAE"*. The *MAE* is however obtain after averaging the stated observations. The error of the mean in absolute terms is express by equation (10) below.

Mean absolute error (*MAE)* = $\frac{1}{n}\sum_{i=1}^{n}|M_i - P_i|$ (10)

where M_i represents the actual amount produced, while P_i represents the predicted amount, while n represents the sample size in the class of figures.

In a related development, the error of the mean in absolute terms as well as the error of the mean in square roots remain repetitively involved at evaluating the capability of a forecasting model (Willmott & Matsuura, 2005) [21]. In another development, Willmott and Matsuura [22] maintain the view of Zhang and Berardi. Who are of the view that the *ERMS* does not adequately points out the average forecasting potentials of a model such that this negative trend displayed by the performance of the *ERMS* can lead to a mean error that could be unreliable [23]. Thus, they declared that the *MAE* is capable of producing satisfactory mean error estimates that could resolve the challenges of the *RMSE*. Hence, in this study we employed both the *ERMS* and *MAE* to take care of the problems associated with the *ERMSE* and *MAE* as raised by Willmott and Matsuura [22], Zhang and Berardi [23] respectively.

IV. Results and Discussions

A. *Descriptive Statistics*

The first data considered in this study out of the stock indexes of the three banks is the average stock prices for Zenith bank. Out of the 3656 data samples of stock indexes for Zenith bank, the process of preprocessing and building models from the collected 3656 data samples employed 1609 data samples to preprocess and build models which is about 44% of the data series. Also, the process of preprocessing, building and forecasting of the remaining data samples out of the 3656 data samples employed a leftover of 2047 data samples in that perspective, which comprised 56% of the total amount of the stock prices data for Zenith bank. Basically, the process of preprocessing a data series implies to prepare the data series for fitting with the model and prediction on the basis of built models implies to forecast sequel to the developed models. Each model is made to create 2047 predictions. The daily average stock price indexes for Zenith Bank is presented in Figure 2 which illustrates the entire depiction of 3656.

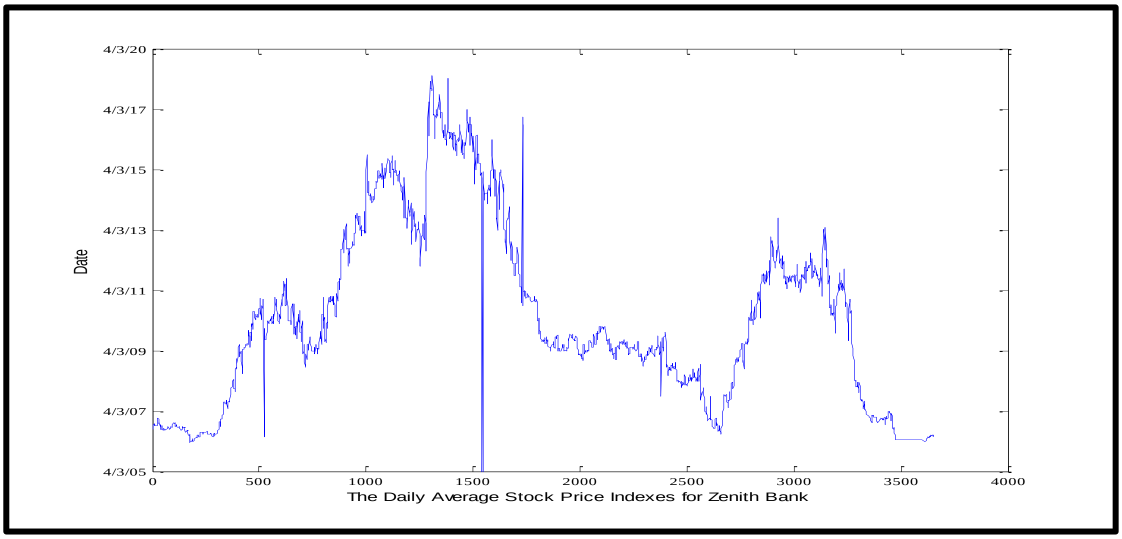

Fig. 2. Diurnal average stock prices for Zenith Bank *PLC.*

The graph of the autocorrelation function on diurnal average stock price indexes for Zenith bank which can also be referred to as sample diurnal average stock price indexes data with 95% confidence bound is shown in Figure 3.

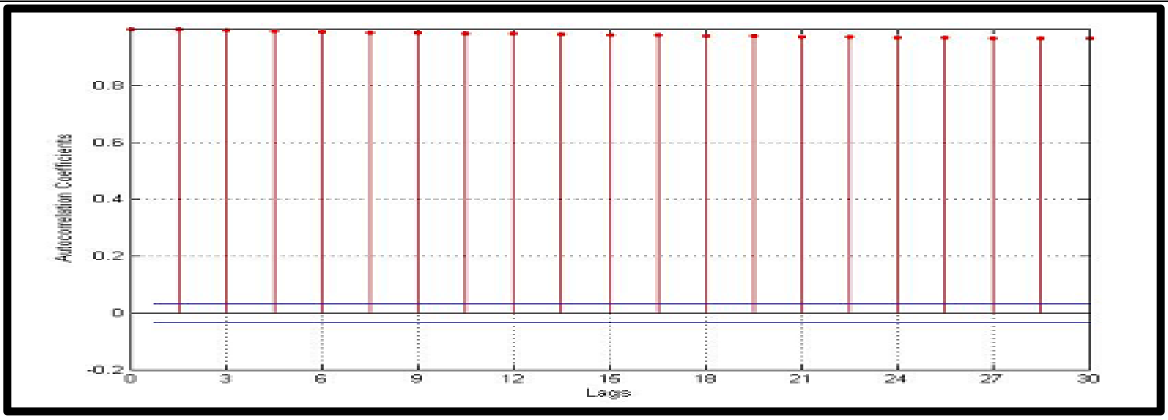

Fig. 3. *ACF* for diurnal average stock prices for Zenith Bank *PLC.*

Figure 2 is graphed by enacting the *plot (xdata)* command in *MATLAB* compiler software, while Figure 3 is graphed by enacting the *autocorr (xdata)* commands in *MATLAB* compiler software respectively. Figure 3 revealed that the daily average stock price indexes for Zenith bank is autocorrelated.

In this study, we are using daily average stock price indexes for three banks. Figures 2, 3 depicts the original data plot for Zenith bank with its autocorrelation function graph respectively. In the same vein, we present original data plots for Guaranty Trust and First banks with their respective autocorrelation function graphs in Figures 4-9 respectively.

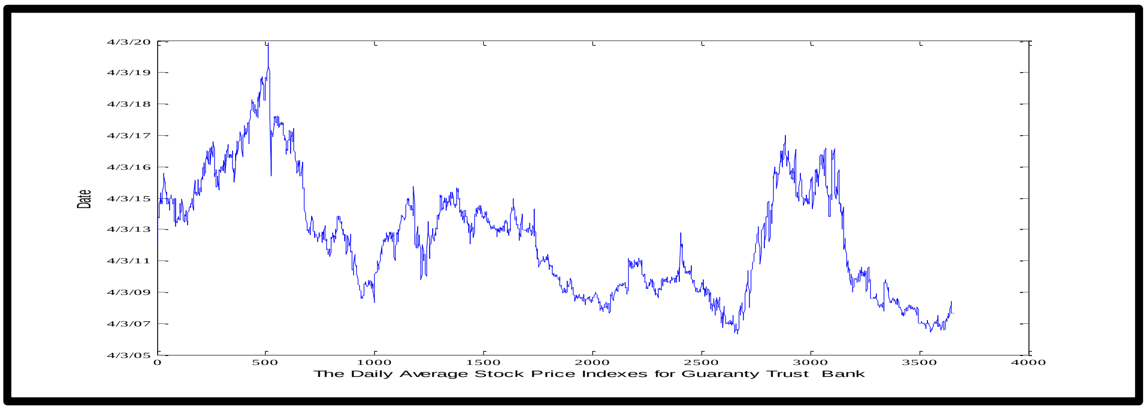

Fig. 4. Diurnal average stock prices for Guaranty Trust Bank *PLC.*

Figure 5 revealed that the daily average stock price indexes for Guaranty Trust Bank is autocorrelated.

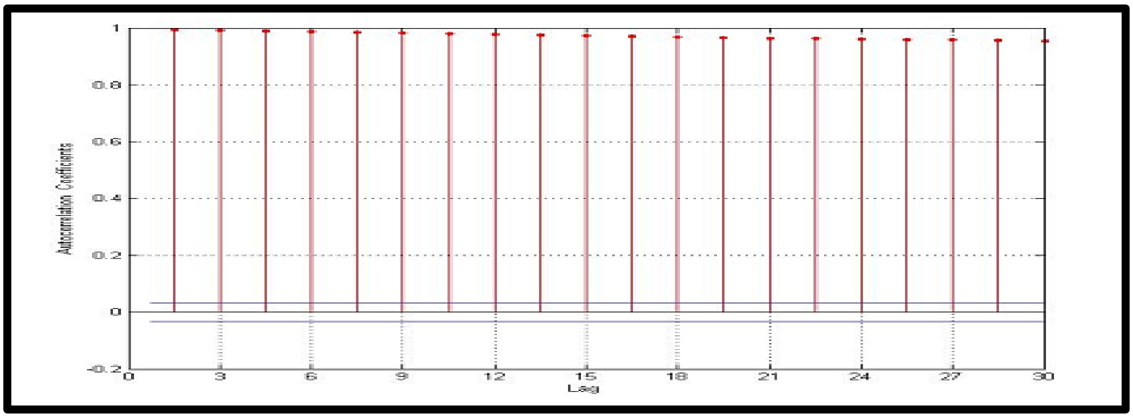

Fig. 5. *ACF* for diurnal average stock prices for Guaranty Bank *PLC.*

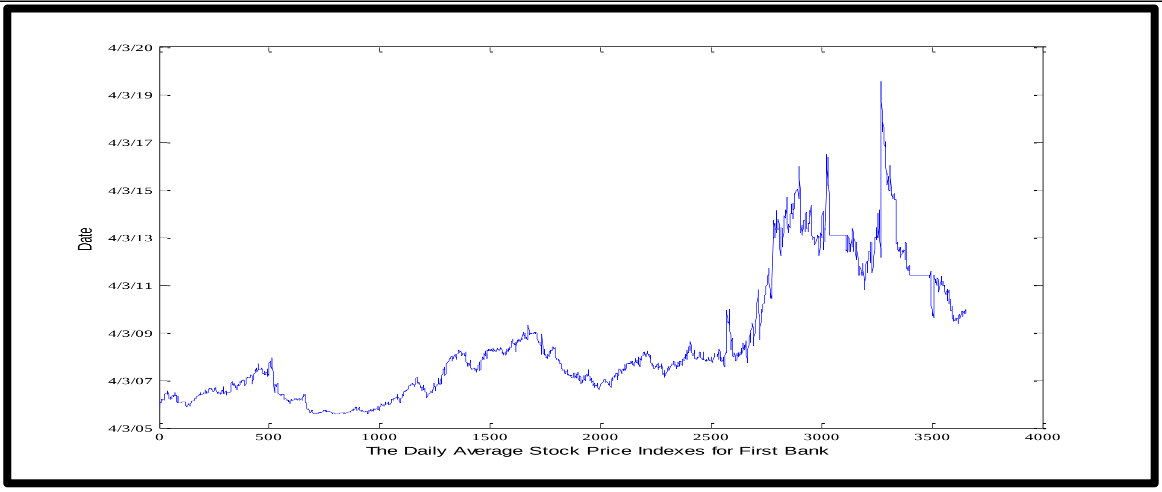

Fig. 6. The daily average stock prices for First Bank *PLC.*

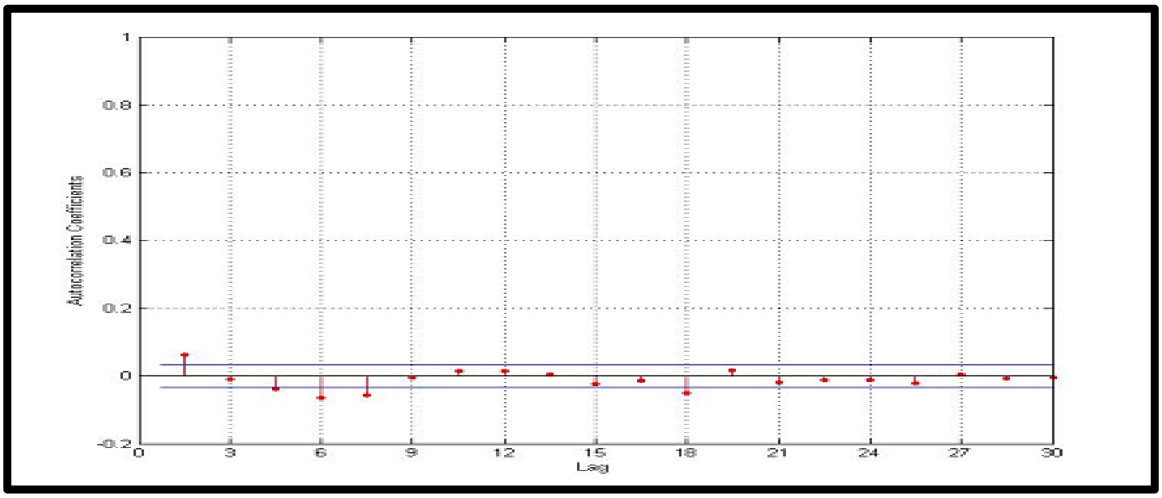

Fig. 7. *ACF* for Diurnal average stock prices for First Bank *PLC.*

Figure 7 revealed that the daily average stock price indexes for First Bank is autocorrelated.

In this study, the stock price indexes for all the three banks are essentially time series observations since they were all recorded at a regular interval of time. Therefore, the data series must be metamorphose into a stationary series before it is simulated into the models for forecasting. Often, a model type is suggested by the pattern of the sample autocorrelation and partial autocorrelation functions. Nevertheless, it is not easy to carve out a model based on Figures 3, 5 and 7. Most often, time series observations are usually presumed a Levy process. The Levy process is a process with independent increments. An increment series is often referred to as the difference series of the original time series data. This process will metamorphose the original series into a stationary series, such that the mean and variance of the original series remains constant overtime, indicating the elimination of volatilities associated with the original series. Suppose $\{Y_t\}$ is the original daily stock price indexes, then $\{X_t = Y_t - Y_{t-1}\}$ is the increment series and since it is obtained by differencing the original time series data, it is also called the difference series.

Figure 8 illustrates the picture of the daily average stock price indexes difference series recordings from Zenith bank. An examination of trend stationary enacted by the Augmented Dickey-Fuller *(ADF)* tests on the difference series of the daily average stock price indexes recordings from Zenith Bank to determine if it is

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stationary. Augmented Dickey-Fuller *(ADF)* tests are implemented by three *MATLAB* commands: $dfTSTest(xdata,\ t)$, $dfTSTest(xdata,\ AR)$ and $dfTSTest(xdata, F)$. The result of *ADF* test indicated the alternative hypothesis was accepted revealing the nonexistence of any statistical significance to agree with the null hypothesis of existence of a unit root on difference series of the daily average stock price indexes recordings from Zenith bank. Hence, we concluded that the difference series of the daily average stock price indexes recordings from Zenith bank for this study is stationary.

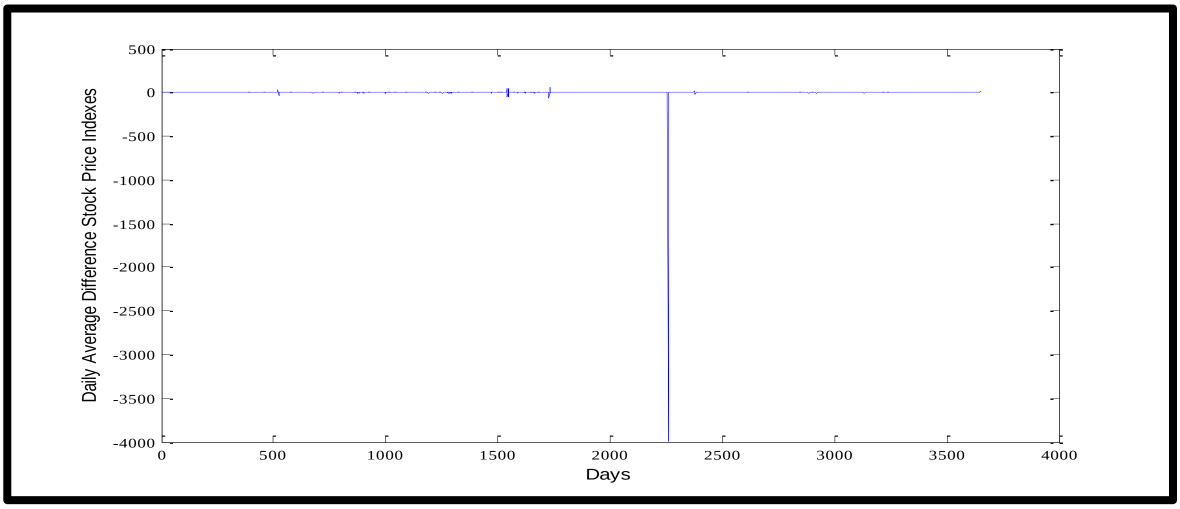

Fig. 8. Difference series of diurnal average stock price indexes for Zenith Bank.

Figure 9 shows a graph on autocorrelation function with difference time series data for daily average stock price indexes recordings from Zenith bank with 95% confidence bound. Figure 9 revealed that the difference series for the daily average stock price indexes recordings from Zenith Bank is autocorrelated. The autocorrelation plot of the first difference series also put forward an order 2 moving average $(MA(2))$ model for the difference series, as one can observe from the autocorrelation plot of the difference series in Figure 9. It is only the first spike that is roughly significant, all autocorrelation functions diminishes rapidly (approximately geometrical decay). Usually an order q moving average $(MA(q))$ model possessed structures of autocorrelati--ons cutting off after lag q. In the same vein, we present graphs on autocorrelation function of difference time series data for daily average stock price indexes recordings from Guaranty Trust and First Banks with 95% confidence bound and their respective autocorrelation function graphs in Figures 10-13 respectively.

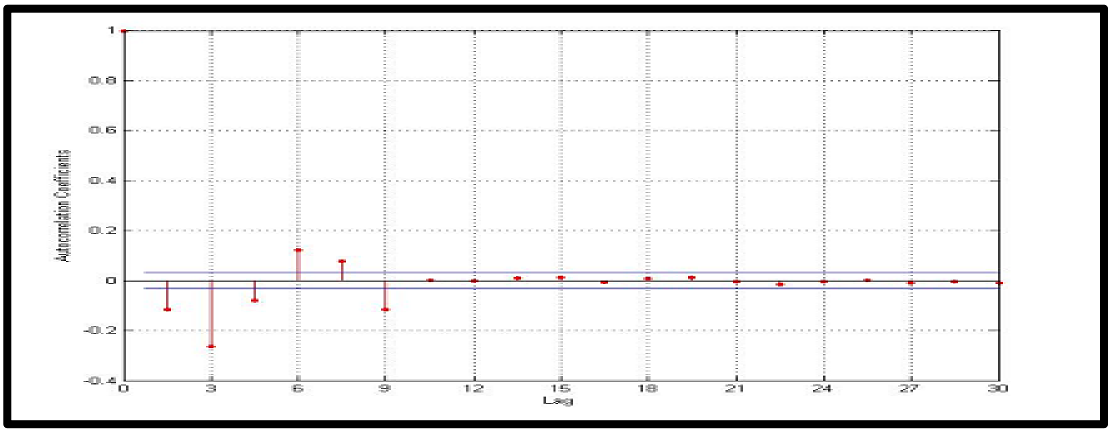

Fig. 9. *ACF* of the difference series of Zenith Bank Data.

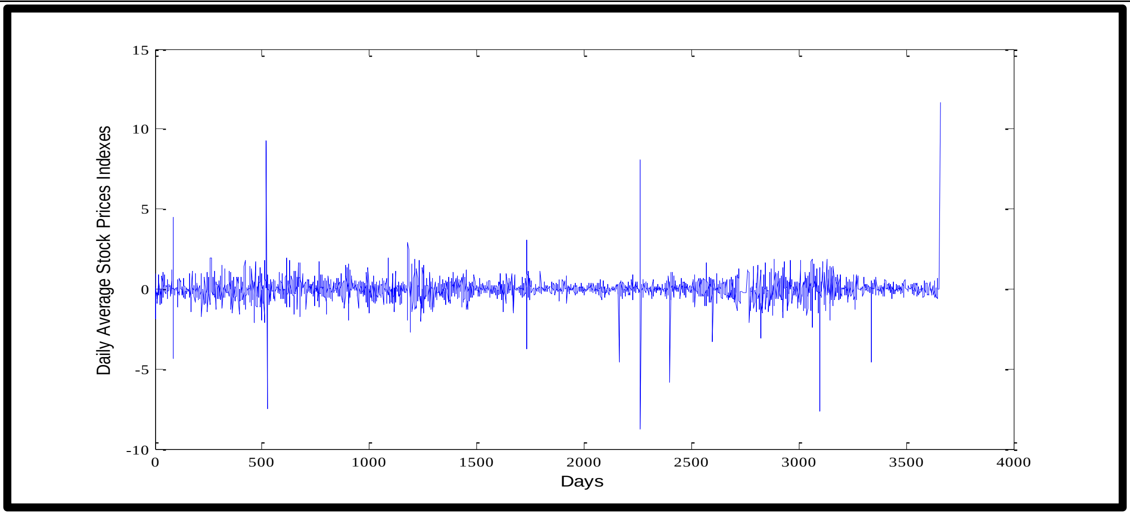

Fig. 10. Difference series of diurnal average stock price indexes for Guaranty Trust Bank

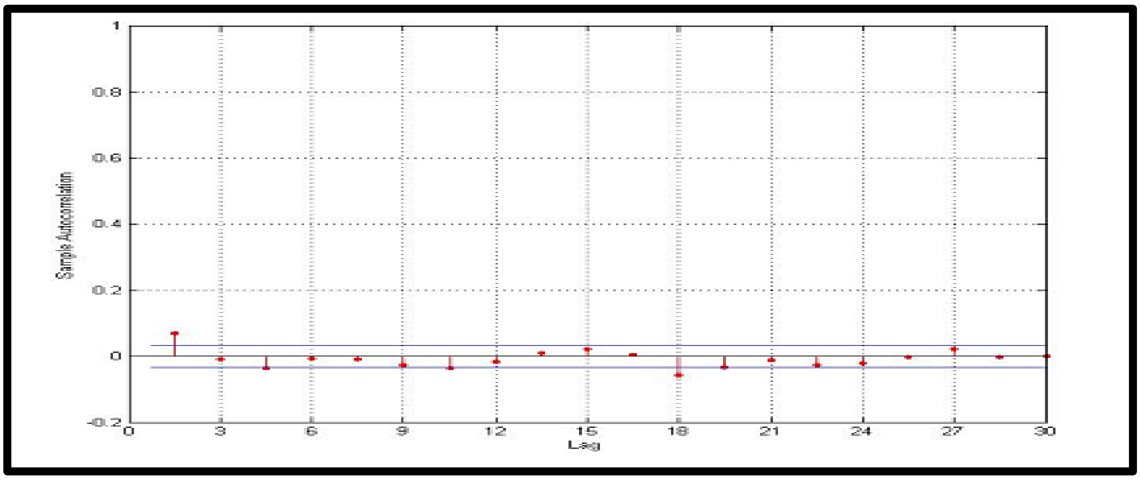

Fig. 11. *ACF* of the difference series of Guaranty Trust Bank Data.

Figure 11 revealed that the difference series for the daily average stock price indexes recordings from Guaranty Trust Bank is autocorrelated.

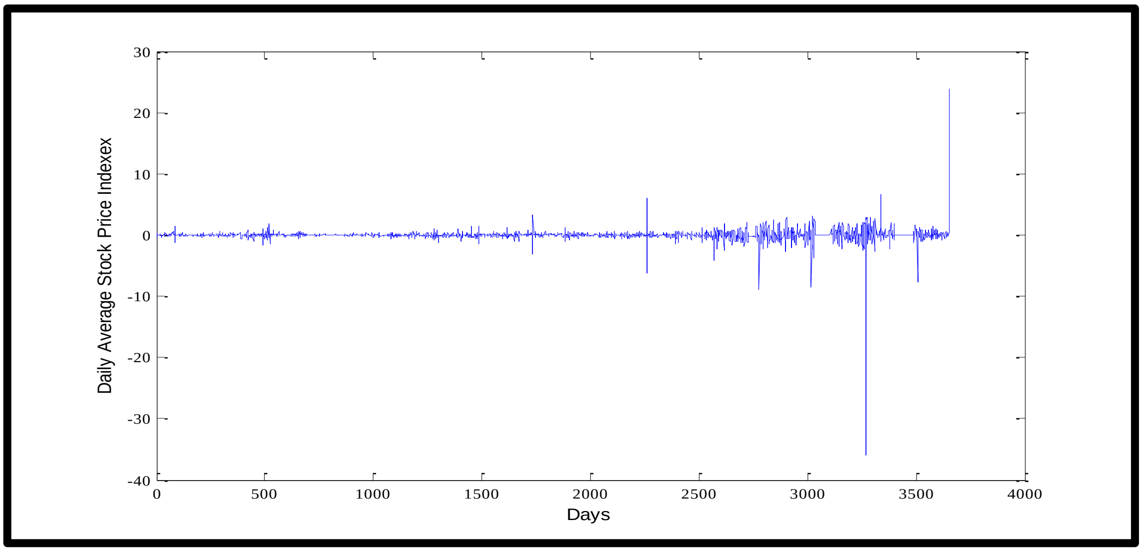

Fig. 12. Difference series of diurnal average stock price indexes for First Bank.

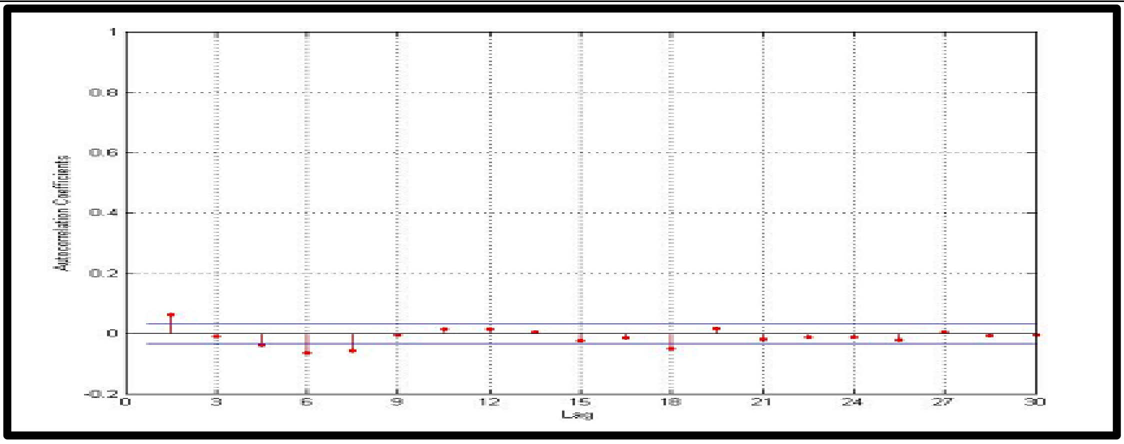

Fig. 13. *ACF* of the difference series of First Bank Data.

Figure 13 revealed that the difference series for the daily average stock price indexes recordings from First bank is autocorrelated. Also, the autocorrelation plots of the first difference series for Guaranty Trust Bank as well as First Bank puts forward an order 2 moving average $(MA(2))$ model for the difference series, as one can observe from the autocorrelation plots of the difference series in Figures 9, 11 and 13 respectively. It is only the first spike that is roughly significant, all autocorrelation functions diminishes rapidly (approximately geometrical decay).

B. *Empirical Results*

Under this subsection of this study, the forecasting performance of the developed hybrid *MLR-CFBNN* technique as in Bianco et al. [24] is compared with the forecasting performance of standalone *MLR* technique as in Thatoi et al. [18] and standalone *CFBNN* technique as in Pwasong and Sathasivam [25]. The comparison process will go through the banks daily average stock price indexes series.

Table 1 shows the forecasting performance of the developed hybrid *MLR-CFBNN* forecasting technique in comparison with the forecasting performance of cascade forward backpropagation neural network *(CFBNN)* method and the forecasting performance of multiple linear regression *(MLR)* method on daily average stock price indexes recordings from Zenith bank. Table 1 also shows the total iterations or total epoch it takes for the hybrid *MLR-CFBNN* forecasting technique in training the data series before it converges and the total time in seconds to attain convergence. The results of Table 1 are the outcomes of the analysis executed on daily average stock price indexes recordings from Zenith bank for 180 sample lengths with 1day, 2 and 3 days ahead prediction. These results are out-of-sample *RMSEs* and *MAEs* of the daily average stock price indexes from Zenith Bank for three input variable hybrid *MLR-CFBNN* models.

Tables 2 and 3 revealed the results respectively for daily average stock price indexes of Guaranty Trust and First banks. The information on Tables 2 and 3 are as obtainable in the information for Table 1.

Table 1. Forecasting performance comparison of Hybrid *MLR-CFBNN* Model with Standalone *MLR* and *CFBNN* Models using Stock Price Indexes for Zenith Bank.

Sample Length			***n* =180**		
Model	**Prediction**	***RMSE***	***MAE***	**Total Epoch**	**Total Time (sec)**
Hybrid *MLR-CFBNN*	1 day	0.772434898	0.303135172	302444	8898.99400000000

Sample Length			***n =180***		
Model	**Prediction**	***RMSE***	***MAE***	**Total Epoch**	**Total Time (sec)**
	2 days	0.77473034	0.303694291	256405	7542.29300000000
	3 days	0.774670013	0.303807574	241801	51800.3159999998
Standalone *MLR*	1 day	0.964542984	0.918481476	*	*
	2 days	0.956884711	0.916195858	*	*
	3 days	0.960957117	0.919607647	*	*
Standalone *CFBNN*	1 day	2.782388119	0.912422786	276708	7288.19399999999
	2 days	2.792470504	0.916026196	263974	17820.7080000000
	3 days	2.790964579	0.924896746	269126	14902.7660000000

Table 2. Forecasting performance comparison of Hybrid *MLR-CFBNN* Model with Standalone *MLR* and *CFBNN* Models using Stock Price Indexes for Guaranty Bank.

Sample Length			***n =180***		
Model	**Prediction**	**RMSE**	***MAE***	**Total Epoch**	**Total Time (sec)**
Hybrid *MLR-CFBNN*	1 day	0.418052978	0.302124799	261615	4316.38700000001
	2 days	0.418038891	0.302109046	263937	4309.82500000002
	3 days	0.418029315	0.302112967	249045	4086.49500000003
Standalone *MLR*	1 day	3.229780168	1.624799816	*	*
	2 days	3.329313168	1.629670167	*	*
	3 days	0.878212217	0.516802074	*	*
Standalone *CFBNN*	1 day	0.605782973	0.345392449	14038634	500786.048999999
	2 days	0.605782971	0.34539152	13713286	707526.913000000
	3 days	0.617652317	0.35256279	282060	11245.2880000000

To evaluate forecasting performances, a computation of both the root of mean square error (*RMSE*) and the mean absolute error (*MAE*) is executed. In this perspective, if data is normally distributed, the forecasts with the minimum error are the optimal forecasts. For data length of 180 for 1 day ahead prediction *RMSE*, the hybrid *MLR-CFBNN* model performs better than other models in all the daily average stock series data sets for Zenith Bank. In a similar vein, the hybrid *MLR-CFBNN* method performs better than the standalone multiple linear regression (*M LR*) and standalone cascade forward backpropagation (*CFBNN*) models in the data series for 1 day ahead prediction *MAE* for 180 sample length for Zenith bank. This is clearly illustrated in Figure 14. To evaluate forecasting performances, a computation of both the root of mean square error (*RMSE*) and the mean absolute error (*MAE*) is executed. In this perspective, if data is normally distributed, the forecasts with the minimum error are the optimal forecasts. For data length of 180 for 1 day ahead prediction *RMSE*, the hybrid *MLR-CFBNN* model performs better than other models in all the daily average stock series data sets for Zenith Bank. In a similar vein, the hybrid *MLR-CFBNN* method performs better than the standalone multiple linear regression (*M LR*) and standalone cascade forward backpropagation (*CFBNN*) models in the data series for 1 day ahead prediction *MAE* for 180 sample length for Zenith Bank. This is clearly illustrated in Figure 14. For 2 days ahead prediction *RMSE* for 180 data sample length, the new hybrid *MLR-CFBNN* performs better for Zenith Bank data than other methods. The reason for the great performance of the hybrid *MLR-CFBNN* technique is because it is characterized by the lowest root mean square error *(RMSE)* and the lowest mean absolute error *(MAE)* as compared to the *RMSEs* as well as *MAEs* of the standalone multiple linear regression (*MLR*) and standalone cascade forward backpropagation (*CFBNN*) models in all the data series for 1 day, 2 days as well as 3 days ahead prediction. In a similar perspective, the hybrid *MLR-CFBNN* outperforms other forecasting techniques for 2 days ahead prediction *MAE* of 180 sample length data sets considered in this study for Zenith Bank. For 3 days ahead prediction *RMSE* for 180 data sample length, the hybrid *MLR-CFBNN* technique performs better than other forecasting techniques in the data set for Zenith Bank. Similarly, for 3 days ahead prediction *MAE* of 180 data sample length, the developed hybrid *MLR-CFBNN* technique outperforms other methods in the data set for Zenith Bank. Table 1 and Figure 14 considered under this subsection further buttress the foregoing assertion.

Table 3. Forecasting performance comparison of Hybrid *MLR-CFBNN* Model with Standalone *MLR* and *CFBNN* Models using Stock Price Indexes for First Bank.

Sample Length			***n =180***		
Model	**Prediction**	***RMSE***	***MAE***	**Total Epoch**	**Total Time (sec)**
Hybrid *MLR-CFBNN*	1 day	0.772434898	0.303135172	305097	5266.08900000002
	2 days	0.77473034	0.303694291	258660	4412.73300000002
	3 days	0.774670013	0.303807574	277163	8412.57900000001
Standalone *MLR*	1 day	3.070212405	1.021849996	*	*
	2 days	3.059400884	1.013316359	*	*
	3 days	2.898432285	0.989349317	*	*
Standalone *CFBNN*	1 day	0.964542984	0.918481476	257973	10734.2040000000
	2 days	0.956884711	0.916195858	257943	10640.6870000000
	3 days	0.960957117	0.919607647	252229	10408.0600000000

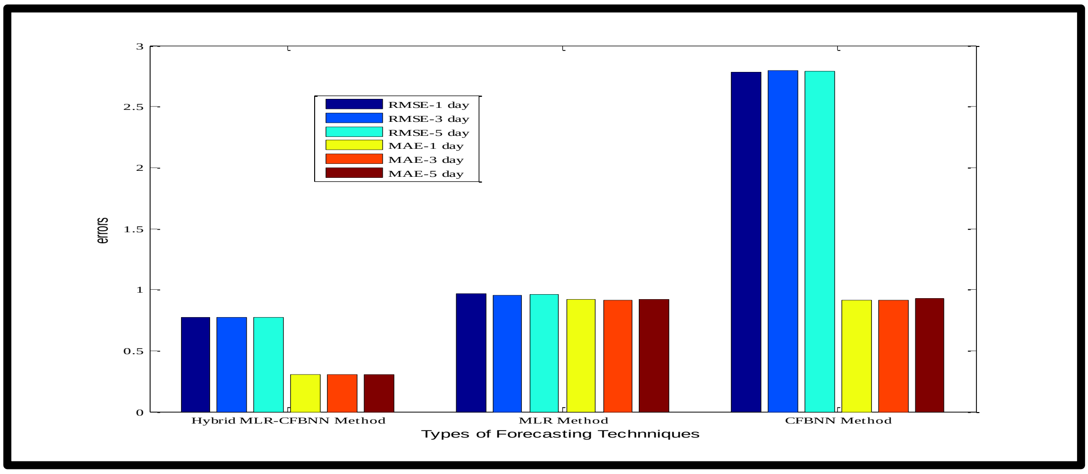

Fig. 14. Comparison of forecasting performance between Hybrid MLR-CFBNN and other forecasting methods on Zenith Bank Daily average stock price series.

The performance of the developed hybrid *MLR-CFBNN* forecasting model has remain steady in beating the performance of standalone multiple linear regression (*M LR*) and standalone cascade forward backpropagation (*CFBNN*) models in the data series for Guaranty Trust and First banks for 1day, 2 and 3 days ahead prediction *MAE* for 180 sample length with respect to the performance functions of *RMSE* and *MAE*, since both errors in the developed hybrid has remain the minimal. Hence, one could observe that the developed hybrid.

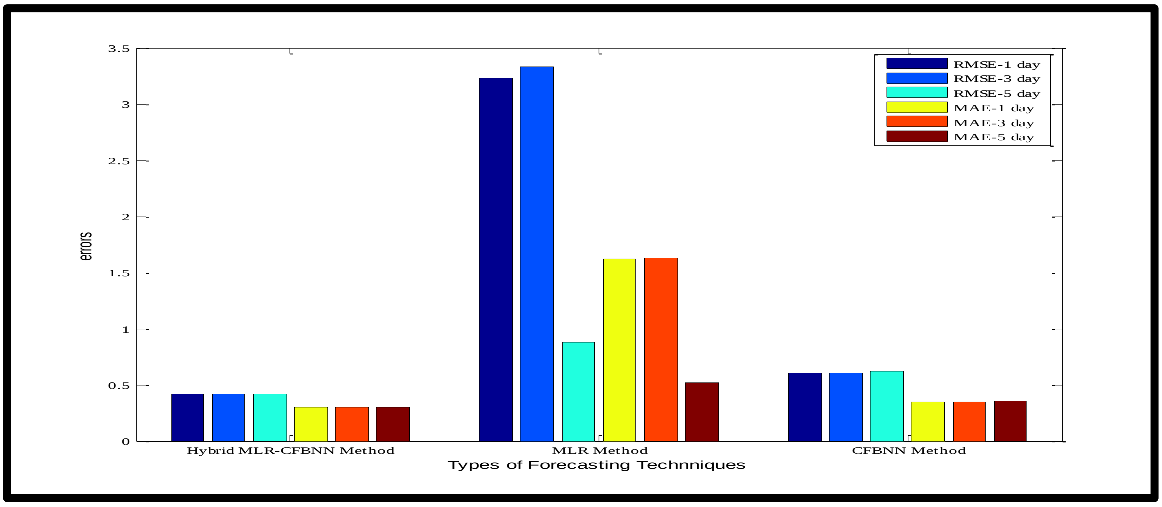

Fig. 15. Comparison of forecasting performance between Hybrid *MLR-CFBNN* and forecasting methods on Guaranty Trust Bank Daily average stock price series.

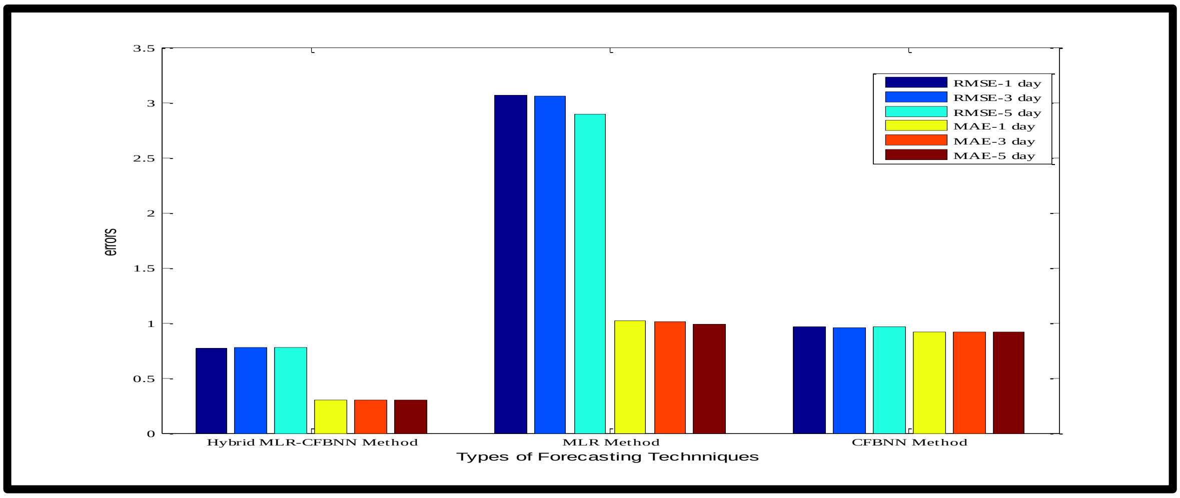

Fig.16. Comparison of forecasting performance between Hybrid *MLR-CFBNN* and other forecasting methods on First Bank Daily average stock price series.

MLR-CFBNN model is more robust and consistent than other standalone forecasting techniques considered in this study for 1day, 2 and 3 days ahead predictions for 180 data sample length. This can also be verified from Tables 2 and 3 as well as Figures 15 and 16 considered under this subsection of the study.

V. CONCLUSION AND RECOMMENDATIONS

This article investigated correlatively a systematic treatise or discourse on the merger of a multiple linear regression *(MLR)* model with a cascade forward artificial neural network model to found a unique hybrid artificial neural network system referred to in this paper as a "hybrid multiple linear regression and a cascade forward backpropagation neural network (*MLR-CFBNN*) technique". This found novel hybrid multiple linear regression with a cascade forward backpropagation neural network (*MLR-CFBNN*) model's predicting capacity was equated to the predicting capabilities two standalone forecasting techniques which are: multiple linear regression (*MLR*) technique and cascade forward backpropagation neural network (*CFBNN*) technique. The developed hybrid method, the existing two standalone forecasting methods were applied on stock price indexes for three different banks in Nigeria. These banks are Zenith Bank *PLC*, Guaranty Trust Bank *PLC* and First Bank *PLC*. The stock price indexes are time series data, since they are described by way of diurnal systematic array. With respect to the figures as well as tables employed in this article, it is pertinent to detect results sprouting from the new found hybrid regression with artificial neural network methods outperforming predicting performances in virtually all ramifications for lone multiple linear regression method and lone cascade forward neural network model of 3 days, 2 days and 1 day forecasts sequel to measurement errors of mean error in absolute terms and mean error in square root terms with data length of 180 observations.

The new found hybrid *MLR-CFBNN* model seems to be vigorous and steady due to the fact that its predicting capability with data length of 180 observations appears to be stable over time. Nonetheless, our new found hybrid *MLR-CFBNN* model is delicate to model response quantities due to unnecessary associations within three response variables or quantities in the model. The intention behind this systematic discourse and correlative treatise with the new found hybrid *MLR-CFBNN* model and the lone multiple linear regression technique as well as the lone cascade forward neural network method is to agree whether the new found hybrid *MLR-CFBNN* model reliably outpaces the forecasting capabilities of lone cascade forward neural network and lone multiple linear regression methods measured in this article. This study is limited to two measures of performance, that is, *RMSE* and *MAE*. Further studies might consider other performance measures such as mean percentage error (*MPE)*, mean absolute percentage error (*MAPE)* symmetric mean absolute percentage error (*SMAPE*), median absolute error (median *AE*), mean absolute scaled error (*MASE*), mean squared normalized error performance function (*MSNE*), mean squared normalized error with regularization performance functions (*MSNEREG*), mean squared error with regularization performance function (*MSEREG*), mean squared error with regularization and economization performance function (*MSEREGEC*), sum of squared error performance function (*SSE*), root mean square percentage error (*RMSPE*), root absolute error (*RAE*), root relative square error (*RRSE*), rank based errors (*RBE*), etc. This study is also limited to 180 sample data length with 1 day, 2 days and 3 days ahead predictions. Further study might consider 200, 400. 800,… respectively with 5, 7, 9,... days ahead predictions.

The develop hybrid model in this study is insightful and a prompt to the Securities and Exchange Commission to predict policies that will be in tandem with speculating the dynamics of stock businesses in Nigeria. Predicting the dynamics of the spread of stock indexes with the hybrid forecasting technique can guarantee stock price stability and ample employment which in turn will produce a steady macroeconomic setting for economic prosperity. This policy would be attained if stock prices strategy is integrated into the macro-economy through the various networks particularly interest rate channel, credit channel and the price level such that the integration mechanism will be one that will escalate the return on investment.

References

[1] J.M. Bates and C.W.J. Granger, "The combination of forecasts", *Operational Research quarterly,* vol. 20, pp. 451-468, 1969,
[2] R.R. Andrawis, A.F. Atiya and H. El-Shishiny, Forecast combinations of computational intelligence and linear models for the NN5 time series forecasting competition. *International Journal of Forecasting,* vol. 27, no. 3, pp. 672-688, 2011.
[3] C.G. Carmichael, A study of the accuracy, completeness, and efficiency of artificial neural networks and related inductive learning techniques, 2001.
[4] R.P. Lippmann, An introduction to computing with neural nets. *ASSP Magazine, of the Institute of Electrical and Electronics Engine-*

*-ers vol.*4, no. 2, pp. 4-22, 1987.

[5] Enke, D. & Thawornwong, S. (2005). The use of data mining and neural networks for forecasting stock returns. *Journal of Expert Systems Applications*, vol. 29, pp. 927-940.

[6] N. Ibrahim, R.R. Abdullah and M. Saripan, Artificial neural network approach in radar target classification. *Journal of Computer Science*, vol. 5, no. 1, pp. 257-262, 2009.

[7] T. Chenoweth and Z. Obradovic, A multi-component nonlinear prediction system for the S&P500 index. *Neurocomputing*. Vol. 10, pp. 275-290, 1996.

[8] R. Pino, J. Parreno, A. Gomez, and P. Priore, Forecasting next-day price of electricity in the Spanish energy market using artificial neural networks, *Journal of Engineering Applications and Artificial Intelligence*, pp. 2153-62, 2008.

[9] C.J. Lu, T.S. Lee, and C.C. Chiu, Financial time series forecasting using independent component analysis and support vector regression. *Decision Support Systems*, vol. 47, no. 2, pp. 115-125, 2009.

[10] C.J. Lu, Hybridizing nonlinear independent component analysis and support vector regression with particle swarm optimization for stock index forecasting, *Neural Computing and Applications*, vol. *23*, no. 7, pp. 2417-2427, 2013.

[11] P.F. Lin, K.P. Lin, C.S. and P.T. Chang, Time series forecasting by a seasonal support vector regression model. *Expert Systems with Applications*. Vol. 37, no. 6, pp. 4261-4265, 2010.

[12] O. Kisi and A. Guven, Daily pan evaporation modeling using linear genetic programming Technique. *Irrigation Science*, vol. 29, pp. 135-145, 2011.

[13] U. Okkan and Z. Ali Serbes, the combined use of wavelet transform and black box models in reservoir inflow modeling, *Journal of Hydrology and Hydromechanics*, vol. 61no. 2, pp. 112-119, 2013.

[14] M. Rajurkar, U. Kothyari and U. Chaube, Modeling of the daily rainfall runoff relationship with artificial neural network, *Journal of Hydrology*, vol. 285, no. 1, pp. 96-113, 2004.

[15] F.M., Tseng, H.C. Yu and G.H. Tzeng, Combining neural network model with seasonal time series arima model, *Technological Forecasting and Social Change*, vol. 69, no. 1, pp. 71-87, 2002.

[16] S. Weisberg, Applied Linear Regression, 3rd edition, John Wiley & Sons, Inc., Hoboken, New Jersey, 2005.

[17] I., Miller, M. Miller, and E. John, Freund's mathematical Statistics. 6th edition, Prentice-Hall of India Private Limited, New Delhi, pp. 391-432, 2003.

[18] D. Thatoi, P Guru, P.K. Jena, S. Choudhury, and H.C. Das, Comparison of cfbp, ffbp, and rbf networks in the field of crack detection. *Modelling and Simulation in Engineering*, vol. 3, pp. 1-13, 2014.

[19] A.K., Sahoo, Y. Zhang and M.J. Zuo, Estimating crack size and location in a steel plate using ultrasonic signals and cfbp neural networks, *Electrical and Computer Engineering, CCECE, Canadian Conference on*, IEEE, pp. 001751-001754. 2008.

[20] S. Saigal and D. Mehrotra, Performance comparison of time series data using predictive data mining techniques, *Advances in Information Mining*, vol. 4, no. 1, 57-66, 2012.

[21] T. Chai and R.R. Draxler, Root mean square error (rmse) or mean absolute error (mae)?–arguments against avoiding rmse in the literature, *Geoscientific Model Development* vol. 7, no. 3, pp. 1247-1250, 2014.

[22] C.J. Willmott and K. Matsuura, Advantages of the mean absolute error (mae) over the root mean square error (rmse) in assessing average model performance. *Climate research*, vol. 30, no. 1, pp. 79, 2005.

[23] G. Zhang and V. Berardi, Time series forecasting with neural network ensembles: An application for exchange rate prediction. *Journal of the Operational Research Society*, vol. 52, no. 6, pp. 652-664, 2001.

[24] V. Bianco, O. Manca and S. Nardini, Electricity consumption forecasting in Italy using linear regression models, *Energy*. Vol. 34, no. 9, pp. 1413-1421, 2009.

[25] A. Pwasong and S. Sathasivam, A new hybrid quadratic regression and cascade forward backpropagation neural network. *Neurocomputing*, Elsevier, vol. 182, pp. 197-209, 2016.

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