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A COMPARATIVE STUDY OF AUTOREGRESSIVE INTEGRATED MOVING AVERAGE AND ARTIFICIAL NEURAL NETWORKS MODELS

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ABSTRACT: *In this study, the forecasting capabilities of nonlinear models as Artificial Neural Networks and linear ARIMA models were compared. The comparison was conducted using the daily data of Nigeria's All Share Index for 11 years. The empirical findings revealed ARIMA (1,1,2) model as the best fit for Nigeria's All Share Index among other Box Jenkins models. This was supported by the most fit statistic test. Also, ANN model with three units in the hidden layer, two lags and the learning rate equal to 0.1, returned as the best fit for the Nigeria All Share Index forecasting. Furthermore, while comparing the performance of the two models, the RMSE of the ARIMA model equivalent to 0.0136 is higher than the RMSE of the ANN model (0.0048), indicating the efficiency of the ANN model. Thus, we can conclude from the above statistics that the ANN model is more efficient. As a result, the study recommends taking advantage of the high capacity of artificial neural networks as a forecasting technique in other fields, such as medical research, genetics research, industrial research, energy, and military research.*

KEYWORDS: ANN, ARIMA, ASI, Time Series.

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INTRODUCTION

Time series analysis in the financial area has been abstract and needs special attention in recent years. The stock markets are examples of systems with complex behaviour and sometimes forecasting a financial time series can be a hard task. Several research studies on stock predictions have been conducted with various solution techniques proposed over the years. The prominent techniques fall into two broad categories, namely statistical and soft computing techniques. Statistical techniques include, among others, exponential smoothing, autoregressive integrated moving average (ARIMA), and generalized autoregressive conditional heteroskedasticity (GARCH) volatility (Wang, Wang, Zhang, & Guo, 2012). The ARIMA model, also known as the Box Jenkins model or methodology, is commonly used in analysis and forecasting. It is widely regarded as the most efficient forecasting technique in social science and is used extensively for time series. The use of ARIMA for forecasting time series is essential with uncertainty as it does not assume knowledge of any underlying model or relationships as in some other methods. ARIMA essentially relies on past values of the series as well as previous error terms for forecasting (Tabachnick & Fidell, 2001). However, ARIMA models are relatively more robust and efficient than complex structural models in relation to short-run forecasting (Meyler, Kenny, & Quinn, 1998).

Artificial neural networks (ANNs), as soft computing techniques, are the most accurate and widely used forecasting models in many areas including social, engineering, economic, business, finance, foreign exchange, and stock problems (Khashei & Bijari, 2010). Its wide usage is due to the several distinguishing features of ANNs that make them attractive to both researchers and industrial practitioners. As stated in Khashei and Bijari (2010), ANNs are data-driven, self-adaptive methods with few prior assumptions. They are also good predictors with the ability to make generalized observations from the results learnt from original data, thereby permitting correct inference of the latent part of the population. Furthermore, ANNs are universal approximators, as a network can efficiently approximate a continuous function to the desired level of accuracy.

Statement of the Problem

The comparison of linear and nonlinear time series modeling has been an aspect of modeling with little research interest, evidenced from the limited literature available for the comparison of these two different time series models, although, ANNs have been found to be very efficient in solving nonlinear problems including those in the real world (Meyler, Kenny, & Quinn, 1998). This is in contrast to many traditional techniques for time series predictions, such as ARIMA, which assumes that the series are generated from linear processes and as a result might be inappropriate for most real world problems that are nonlinear (Zhang, Patuwo, & Hu., 2009) There is a growing need to solve highly nonlinear, time variant problems as many applications such as stock markets are nonlinear with uncertain behaviour that changes with time (Fuller, 1995). ANNs are known to provide competitive results to various traditional time series models such as ARIMA model (Jain & Kumar, 2007). These concerns thus bring about the research’s aim and objectives which are stated below.

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Aim and Objectives

The aim of this study is to compare the performances of ANN and ARIMA models for a case of stock price index prediction, which will also further clarify and/or confirm contradictory opinions reported in literature about the superiority of each of the models over one another.

The specific objectives of this study are:

i. To model with stock price index (all share index) data for Nigeria stock exchange with the linear (ARIMA) and nonlinear (ANN) time series models

ii. To examine the prediction strength of the linear and nonlinear model in the fitting stock returns over a long period of time.

The remaining parts of this paper were structured as follows: Section 2 discusses reviewed works of literature; Section 3 presents the methodologies employed in the study; Section 4 presents data and empirical results; and the final section concludes the study.

LITERATURE REVIEW

The search for efficient stock price prediction techniques is profound in literature. This is motivated partly by the dynamic nature of the problem as well as the need for better results. Tansel *et al.* (1999) compared the performance of linear optimization, ANNs, and genetic algorithms (GAs) in modeling time series data based on modeling accuracy, convenience, and computational time. The study revealed that linear optimization techniques gave the best estimates with GAs providing similar results if the boundaries of the parameters and the resolution were carefully selected, while NNs gave the worst estimates. The work reported in Lee, Sehwan, and Jongdae (2007) also compared the forecasting performance of ARIMA and ANN models in forecasting the Korean Stock Price Index. The ARIMA model generally provided more accurate forecasts than the back propagation neural network (BPNN) model used. This is more pronounced for the midrange forecasting horizons. Merh *et al.* (2010) presented a comparison between hybrid approaches of ANN and ARIMA for Indian stock trend forecasting, with many instances of the ARIMA predicted values shown to be better than those of the ANNs predicted values in relation to the actual stock value. Sterba and Hilovska (2010) argued that ARIMA model and ANN model achieved good prediction performance in many real world applications, especially time series prediction. Experimental results obtained by the authors further revealed that ARIMA model generally performs better in the prediction of linear time series, while ANNs perform better in the prediction of nonlinear time series. In a similar study for financial forecasting reported in Lahane (2008), ANNs model was shown to perform better than ARIMA model in value forecasting, while ARIMA model performed better than ANNs in directional forecasting.

Yao *et al.* (2009) compared the stock forecasting performance of ANN and ARIMA models and showed that the ANN model obtained better returns than the conventional ARIMA models. Similarly, Hansen *et al.* (1999) compared the prediction performance of ANNs and ARIMA on time series. The result shows that the ANNs outperformed ARIMA in predicting stock movement direction as the latter was able to detect hidden patterns in the data used. Prybutok *et al.* (2000) also compared the forecasting performance of ANN and ARIMA models in

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forecasting daily maximum ozone concentration. Empirical results obtained also showed that the ANN model is superior to the ARIMA model. Wijaya *et al.* (2010) did a similar comparison based on the Indonesian stock exchange and got better accuracy with ANN than the ARIMA model. More works of literature have shown the prevalent use of ANNs as an effective tool for stock price prediction (Tsanga *et al.,* 2007). This makes ANN a promising technique or potential hybrid for the prediction of movement in time series.

Empirical results show that Artificial Neural Networks (ANNs) can be more effectively used to make better forecasts than the traditional methods since stock markets have complex structures that are nonlinear, dynamic and even chaotic. Due to these reasons, ANNs can increase the forecast performance due to a learning process of the underlying relationship between the input and output variables and their ability to discover nonlinear relationships. Despite all this, ANNs also have some limitations; for instance, error functions of ANNs are usually complex, cumulative, and commonly they have many local minima, unlike the traditional methods. So, each time the network runs with different weights and biases, it arrives at a different solution.

Many studies have been focused on the debate in the sense that the traditional approach in time series forecasting when applied in series with a good behaviour can be more efficient but when applied in series that present some noise and complexity (Enke, 2005; Ho *et al.,* 2002), nonlinear modeling techniques may overcome these problems. Enke (2005) points out that there is no evidence to support the assumption that the relationship between the stock returns and the financial variables are perfectly linear, due to the significant residual variance of the stock return from the prediction of the regression equation. And, therefore, it is possible that nonlinear models (for instance, ANNs) are able to explain this residual variance and produce more reliable predictions. Despite all of this, the choice between one method and another is not an easy task. A literature review points out that increasing complexity does not necessarily increase accuracy. Sometimes, the traditional statistics can be applied and present a higher performance. Gooijer and Hyndman (2006) point out that some authors stress the importance that future research needs to be done in order to define the frontiers where ANNs and the traditional methods can be more effective with a greater accuracy in relation to each other. For some tasks, neural networks will never replace traditional methods, but for a growing list of applications, the neural architecture will provide either an alternative or a complement to these other techniques.

However, literature has shown a different view on the relative performance and superiority of ARIMA and ANNs models to time series prediction, especially for different data used, hence the need for further study that can help unify a coherent view on the better methodology. This study therefore seeks to further clarify the divergent opinions reported in literature on the superiority of ANN model over ARIMA model and vice versa in the effective prediction of stock prices. Results obtained are based on empirical study on time series stock prediction using data from various Nigeria Stock Exchange.

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METHODOLOGY

ARIMA Modeling Procedure and Algorithm

After doing some exploratory analysis of the data series, we worked with R Expert Modeling – Time Series Analysis in order to determine the best ARIMA model for all the data series. The ARIMA Expert Model has the following structure:

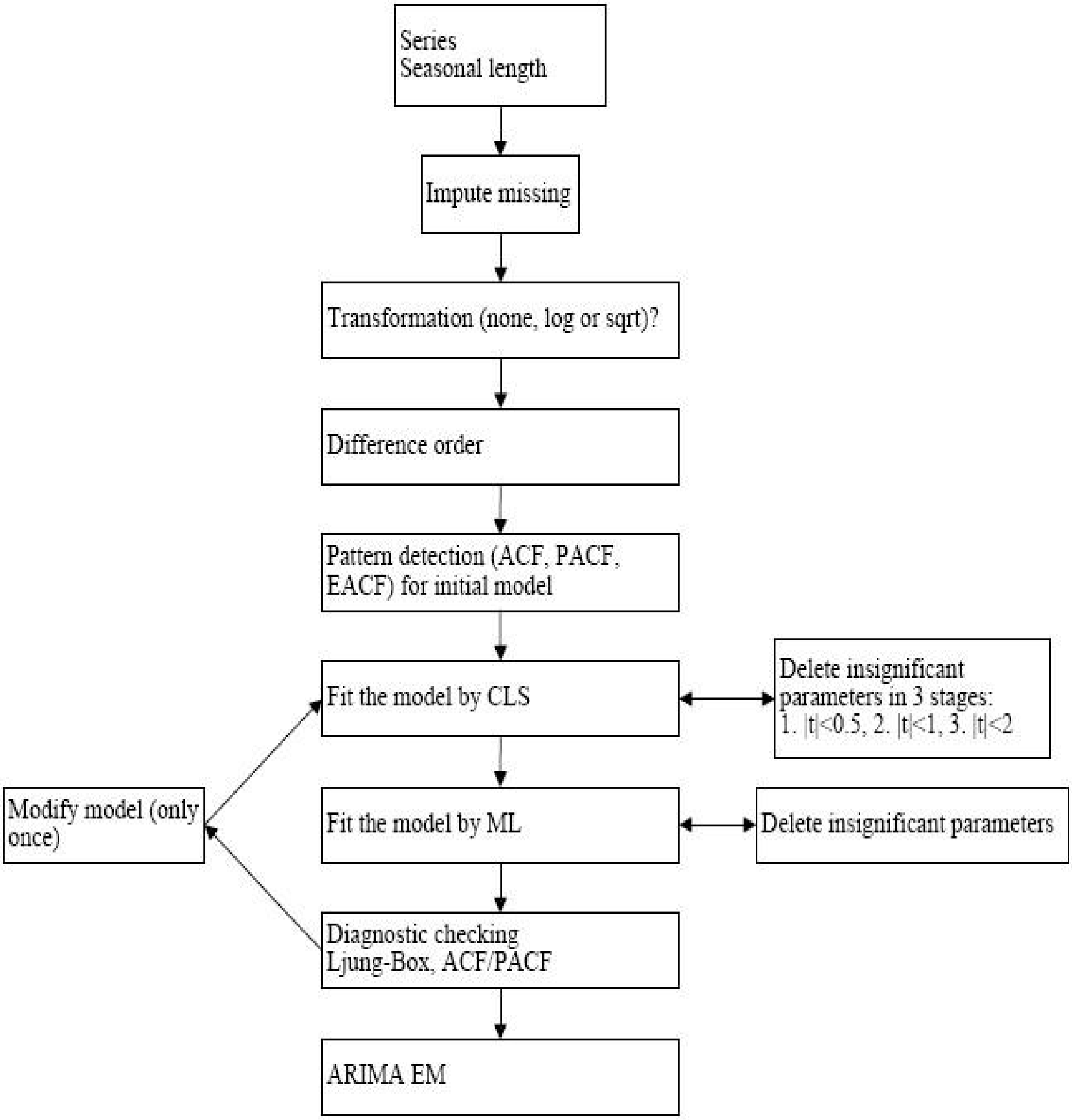

Figure 1: ARIMA Model Detection

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Through this procedure, we applied the Box-Jenkins methodology and in the step related to the pattern detection for initial model Autocorrelation Function (ACF) and Partial Autocorrelation Coefficient (PACF), we determined the adequate ARIMA model (p,d,q)(P,D,Q) incorporating both seasonal and non-seasonal levels.

The Box-Jenkins modeling procedure consists of three stages: identification, estimation and diagnostic checking. (1) At the identification stage, a set of tools are provided to help identify a possible ARIMA model, which may be an adequate description of the data. (2) Estimation is simply the process of estimating this model. (3) Diagnostic checking is the process of checking the adequacy of this model against a range of criteria and possibly returning to the identification stage to pre-specify the model. The distinguishing stage of this methodology is identification.

This approach tries to identify an appropriate ARIMA specification. It is not generally possible to specify a high order ARIMA model and then proceed to simplify it as such a model will not be identified and so cannot be estimated. The first stage of the identification process is to determine the order of differencing, which is needed to produce a stationary data series. The next stage of the identification process is to assess the appropriate ARMA specification of the stationary series. For a pure autoregressive process of lag p, the partial autocorrelation functions up to lag p will be the autoregressive coefficients, while beyond that lag we expect them all to be zero. So in general there will be a 'cut of' at lag p in the partial autocorrelation function. The correlogram on the other hand will decline asymptotically towards zero and not exhibit any discrete 'cut of' point. An MA process of order q, on the other hand, will exhibit the reverse property.

Artificial Neural Network Modeling Procedure

In this case, we employ ANNs to forecast next day returns. One of the main reasons that neural networks in the past decades increased in popularity is due to the fact that these models have been shown to be able to approximate almost any nonlinear function. Thus, when applied to series which are characterized by nonlinear relationships, neural networks can detect these and provide a superior fit compared to linear or even non-linear traditional models.

The neural networks used in this analysis are feed forward multilayer perceptron which employ a sigmoid transfer function. We analyzed the results of four feed forward (known as multilayer perceptron) neural networks:

- Quick method: When the quick method is selected, a single neural network is trained. By default, the network has one hidden layer containing max 3 (ni + no) / 20 neurons, where ni is the number of input neurons and no is the number of output neurons;
- Dynamic method: The topology of the network changes during training with neurons added to improve performance until the network achieves the desired accuracy. There are two stages to dynamic training: finding the topology and training the final network;

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- Multiple method: Multiple networks are trained in pseudo parallel fashion. Each specified network is initialized and all networks are trained. When the stopping criterion is met for all networks, the network with the highest accuracy is returned as the final model. That is, at the end of training, the model with the lowest RMS error is presented as the final model;

- Prune method: That is, conceptually, the opposite of the dynamic method. Rather than starting with a small network and building it up, the prune method starts with a large network and gradually prunes it by removing unhelpful neurons from the input and hidden layers. Pruning proceeds in two stages: pruning the hidden neurons and pruning the input neurons. Pruning is carried out after a while if there is no improvement. Before initially pruning, or after any pruning, the network will run for a number of cycles, specified by the persistence.

To train a neural network, it is important to incorporate input neurons. Several studies showed that in econometric application it is common to use the p lagged variables directly as linear regressors.

$$\gamma_t = \emptyset_0 + \chi_t^{1}\emptyset + \sum_{j=1}^{q} \quad \beta G\left(\chi_t^{1} \; \gamma_j\right) + \varepsilon i \qquad (1)$$

The performance alternative models were evaluated with about 30% of all the data records in each series, evaluating how well competing models generalize outside of the data set used for estimation. This option was also taken due to the over training. To prevent over-training, it is useful to train the network with two sets—training and validation—and accuracy is estimated based on the validation set.

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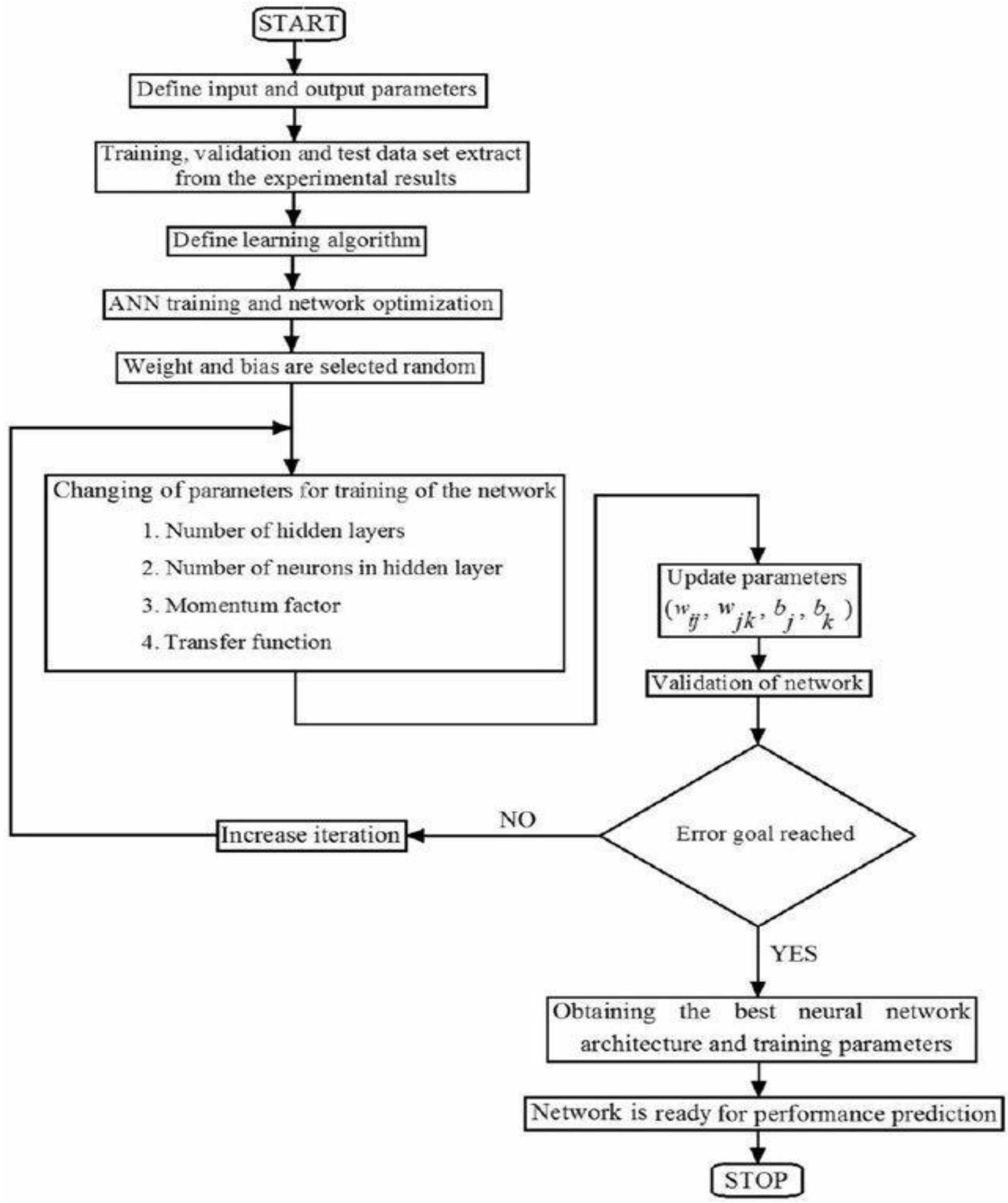

Figure 2: ANN Algorithm/Flowchart

Comparison Between Neural Network and ARIMA Results

To compare the results, we followed the approach of analyzing the mean errors in the models. First, we will look at the minimum error and the maximum error between the observed values and the estimated ones and also, the mean absolute error that shows the average of the absolute values of the errors across all records, indicating the average magnitude of error, independent

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of the direction. And finally, we will show the linear correlation between the predicted and actual values. This statistic varies between –1.0 and 1.0. Values close to +1.0 indicate a strong positive association, so that high predicted values are associated with high actual values and low predicted values are associated with low actual values. Values close to –1.0 indicate a strong negative association, so that high predicted values are associated with low actual values, and vice versa. Values close to 0.0 indicate a weak association, so that predicted values are more or less independent of actual values.

Empirical Results

This section presents the results from the data analysis of Nigeria's All Share Indexes when modeled with ARIMA and ANN accordingly. It also presents the model comparison properties.

Data Source

The data used in this study were obtained from publications of the Nigeria's Securities and Exchange Commission in 2019. The observations are daily time series of All Share Index and are ranged from January 1st, 2008 to December 31st, 2018, which yields a total of observations as n = 2870. Table 1 represents some descriptive statistics of the time series. We observe that the mean of the time series equals 31695.707, the median of the time series is 28959.25, the standard error of the time series is 178.941, the sum of the observation is 399871.6, and deviation of the time series is 9586.319.

This time series represents the indices of stock prices (All Share Index). The original data were transformed using the natural logarithm (see Figure 4), in order to reduce the impact of outliers. One of the advantages of using this transformation is the fixation of variation of the time series that allows no loss of important information from the data. Therefore, the time series that will be used in the analysis is the natural logarithm of the stock price index of Nigeria. Figure 3 below represents the time series which will be analyzed and indicates that it is a non-stationary time series. This series varies randomly over time and there is no global trend or seasonal note. We note here the sharp decline in the stock market at the end of the year 2008 as it is a period of the world economic crisis which affected all global financial markets.

Table 1: Descriptive Statistics of NSE-ASI

			Statistic	Std. Error
NSEASI	Mean		31695.7076	178.94138
	95% Confidence Interval for Mean	Lower Bound	31344.8409	
		Upper Bound	32046.5743	
	5% Trimmed Mean		30737.9166	
	Median		28959.2500	
	Variance		91897449.784	
	Std. Deviation		9586.31576	
	Minimum		19732.34	
	Maximum		66371.20	

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	Range	46638.86	
	Inter quartile Range	12142.20	
	Skewness	1.355	.046
	Kurtosis	1.965	.091

Source: Researchers' Compilations

Figure 3: Graphical Presentations of the Stock Price Index Time Series

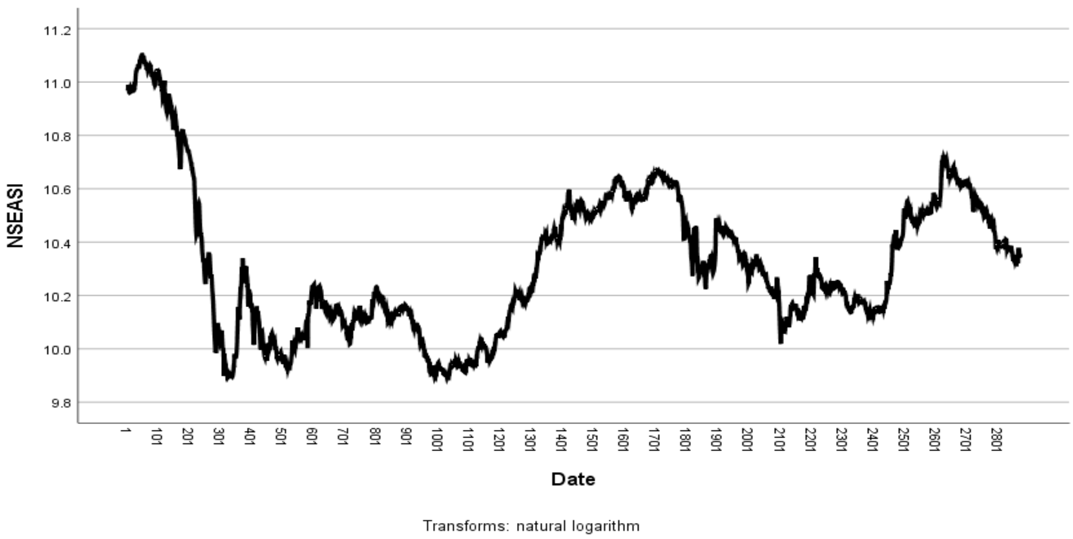

Figure 4: Time Series Plot of the Stock Price Index Natural Logarithm

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Empirical Results

As displayed in Figure 5, the autocorrelation function refers to all values shown which are "significantly far from zero", and the only pattern is a linear decrease with increasing lag; the sample PACF is also indeterminate, and is cut off after the second lag. This means that we are dealing with a typical correlogram of a non-stationary time series.

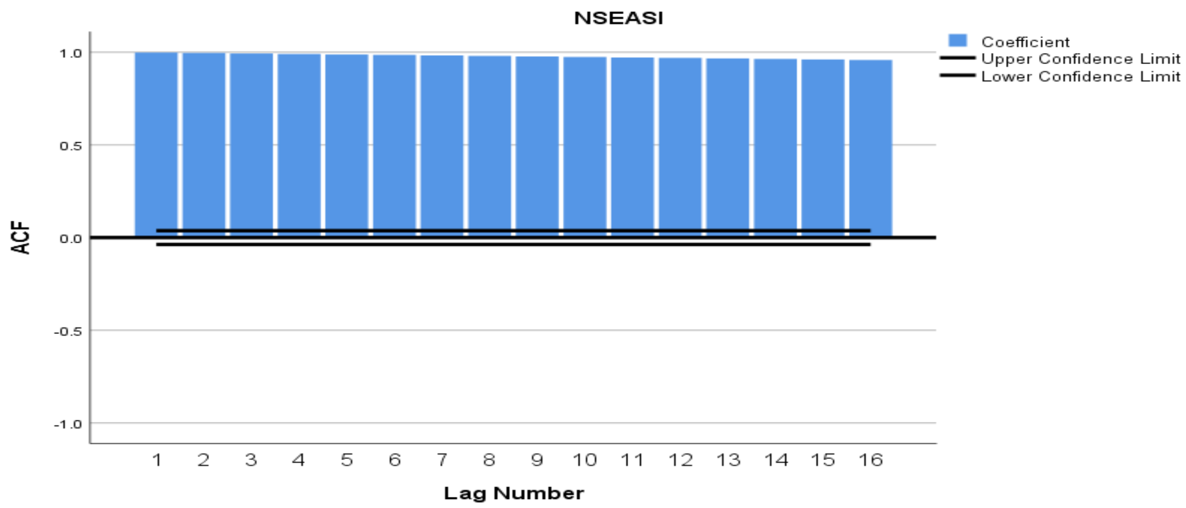

Figure 5: The ACF Plot of the Stock Price Index Natural Logarithm

We use the first difference of the natural logarithm series of the data in order to obtain stationarity. Figure 6 below illustrates the first difference of natural logarithm series.

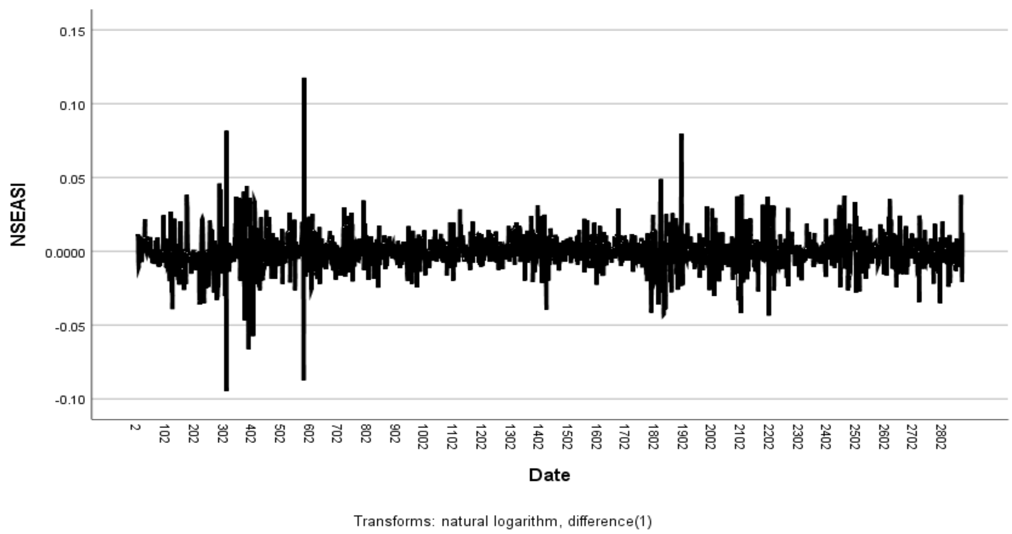

Figure 6: Graphical Display of the 1st Differencing of the Natural Logarithm of the Stock Price Index

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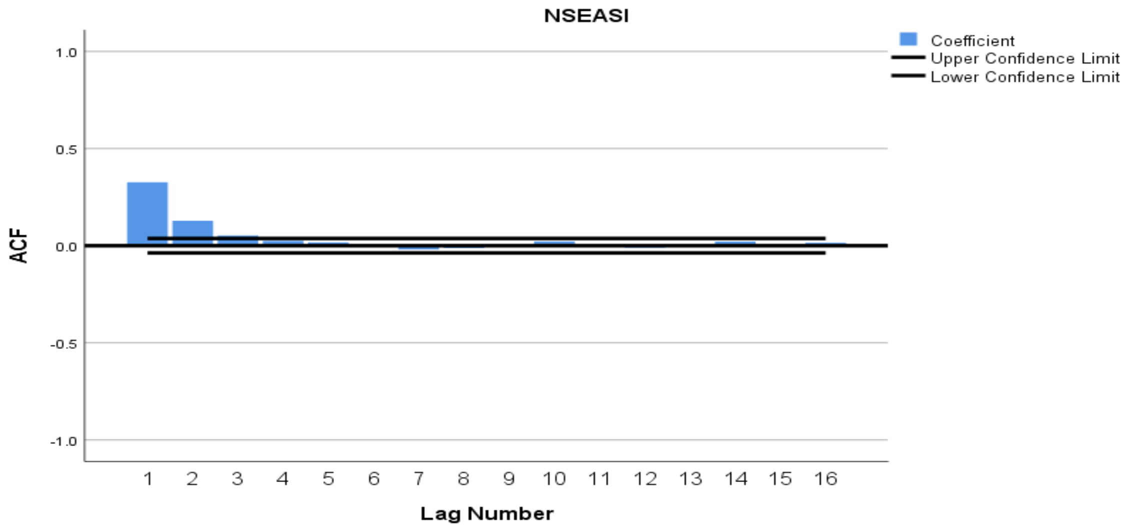

Figure 7: The ACF Plot of the 1st Differenced Stock Price Index Natural Logarithm

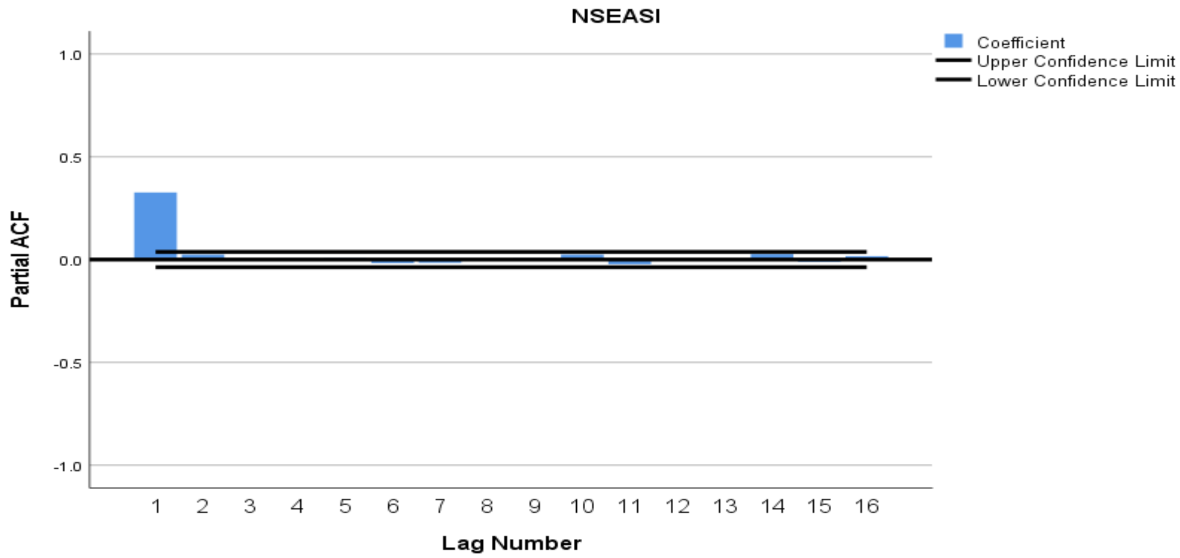

Figure 8: The PACF Plot of the 1st Differenced Stock Price Index Natural Logarithm

By looking at the correlogram of the first difference of the natural logarithm series in Figures 7 and 8, we can say it has become stationary. Also, we can test the stationary through the KPSS test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992), which has recently become popular in econometrics, as it is quite efficient and easy to interpret.

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Table 2: The KPSS Stationarity Check

Lag Truncation Parameter	9		
Test Statistic	1.97037		
Level of Significance	10%	5%	1%
Critical values	0.347	0.461	0.743

Source: R Console

As revealed in Table 2, since the Test statistics value of 1.97 is greater than the critical value at 5% level of significance, we conclude that the series is stationary at the first difference (p, 1, q).

Fitting ARIMA(p,1,q) for the All Share Index

For the time series of differenced Stock Price Index natural logarithm correlogram presented in Figure 7 and 8, it is possible to note a significant autocorrelation and PAC at lag 1. But for a mixed ARMA model, its theoretical ACF and PACF have infinitely many nonzero values, making it difficult to identify mixed models from the sample ACF and PACF.

There are several graphical tools to facilitate identifying the ARMA orders. These include the corner method (Becuin *et al.,* 1980), the extended autocorrelation (EACF) method (Tsay & Tiao, 1984), and the smallest canonical correlation method (Tsay & Tiao, 1985), among others. We applied the EACF method for the underlying differenced time series and the results of different estimates of p and q from Figures 7 and 8. We can observe that appropriate models for the series may be ARIMA (1,1,1) and ARIMA (1,1,2).

Therefore, we will estimate parameters for the two models, and diagnose the best model that may predict future values for the stock prices among these models. The results for this analysis showed that the best model is the ARIMA (1,1,2) as can be seen in Table 3, since this model has lower values for the Fit Statistics than the ARIMA (1,1,1) model.

Table 3: The Fit Statistic for ARIMA (1,1,1) and ARIMA (1,1,2) models

Fit Statistic	Model Type		Better
	ARIMA(1,1,1)	ARIMA(1,1,2)	
Stationary R squared	0.107	0.107	Same
R squared	0.999	0.999	Same
RMSE	328.325	328.389	ARIMA(1,1,1)
MAPE	0.698	0.698	Same
MaxAPE	11.289	11.282	ARIMA(1,1,2)
MAE	217.868	217.863	ARIMA(1,1,2)

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MaxAE	2822.769	2821.130	ARIMA(1,1,2)
Normalized BIC	11.596	11.599	ARIMA(1,1,1)

Source: Compilation from R Console Outputs

By using R-Console, the parameters of the best ARIMA model were determined as follows:

Table 4: ARIMA(1,1,2) Model Parameters Estimation

					Estimate	SE	t	Sig.
NSEASI Model_1	NSEASI	Natural Logarithm	Constant		.000	.000	.690	.490
			AR	Lag 1	.410	.132	3.112	.002
			Difference		1			
			MA	Lag 1	.092	.133	.689	.041
				Lag 2	.006	.047	.133	.038

Source: R Console

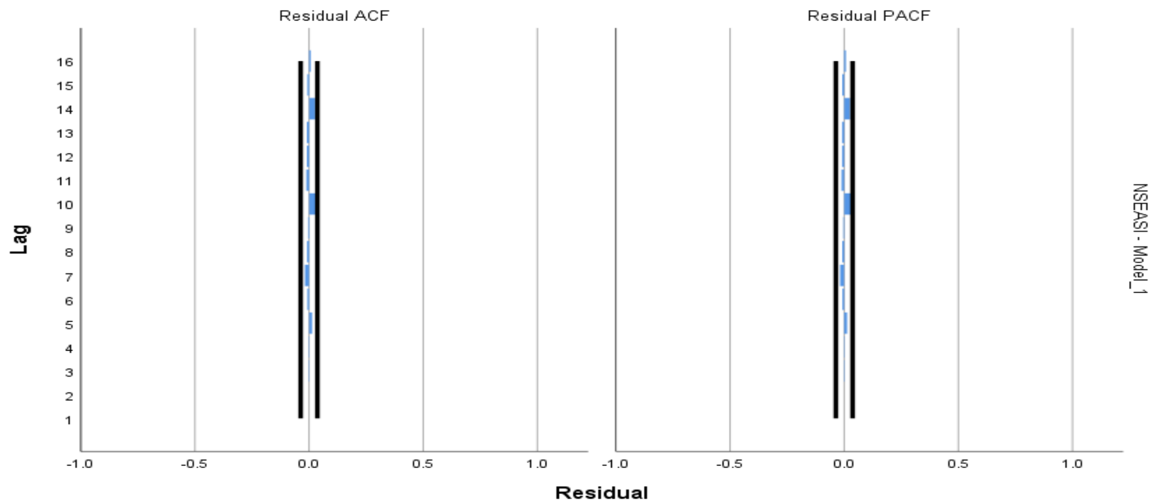

Figure 9: Diagnostic Display for the ARIMA (1,1,2) Model

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Now the ARIMA (1,1,2) model has been fitted to the series of stock price index (All Share Index). Investigating the results of this fit, all coefficients are significant and the diagnostic model suggests that this model is suitable. Let Y_t denote the Diff(LOGNIG), then our tentatively identified ARIMA model is:

$$\hat{Y} = Y_{t-1} + 0.410(Y_{t-1}) - 0.092e_{t-1} - 0.006e_{t-2} \qquad (2)$$

Using this model for forecasting, we get the following results: From the results in the Table 5 and Figure 10 below, which illustrate the prediction of the last ten values of the time series and compare them with last ten actual values with 95% forecast limits, we note that the first three values only close to the actual values and then the rest of the forecast shall revert to the mean of the series, since the model does not contain a lot of autocorrelation, the forecasts quickly settle down to the mean of the series. The forecast limits contain all of the actual values.

Table 5. Forecasting Results of ARIMA (1,1,2) Model

Day	Actual	ARIMA Forecast
2861	30822.33	30465.48
2862	30704.98	30689.57
2863	30802.9	30559.56
2864	30773.64	30665.76
2865	31967.01	30665.76
2866	31967.01	30665.76
2867	31967.01	30665.76
2868	31692.63	31833
2869	31037.72	31545.86
2870	31430.5	31545.86

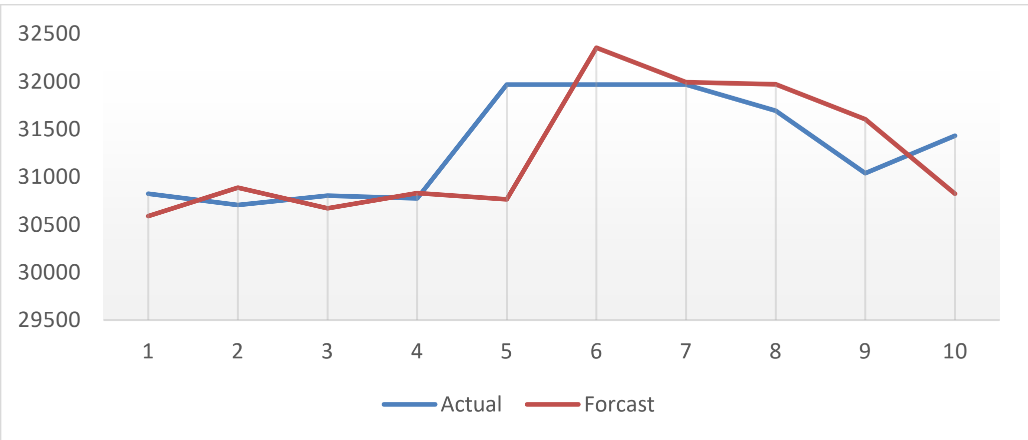

Figure 10: Plot of the ARIMA(1,1,2) Model Forecast Results

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Fitting the Artificial Neural Network Model for the All Share Index

For fitting ANN model for the time series, as described in the previous section using R software. In applying ANN, the percentage of observations for training, which must have the same number of observations as we have in ARIMA for training, is determined, so we have increased in a series of observations. Thus, we have a 90% for training, and 10% for comparison in the prediction. The fitted ANN model is presented in Figure 11.

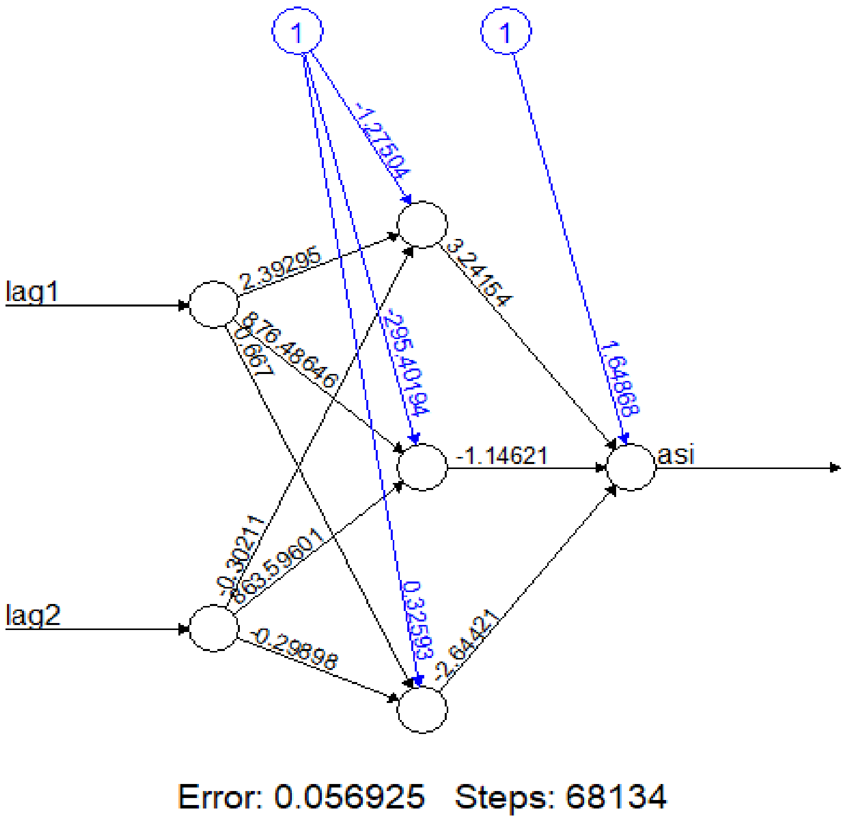

Figure 11: Fitted ANN Model

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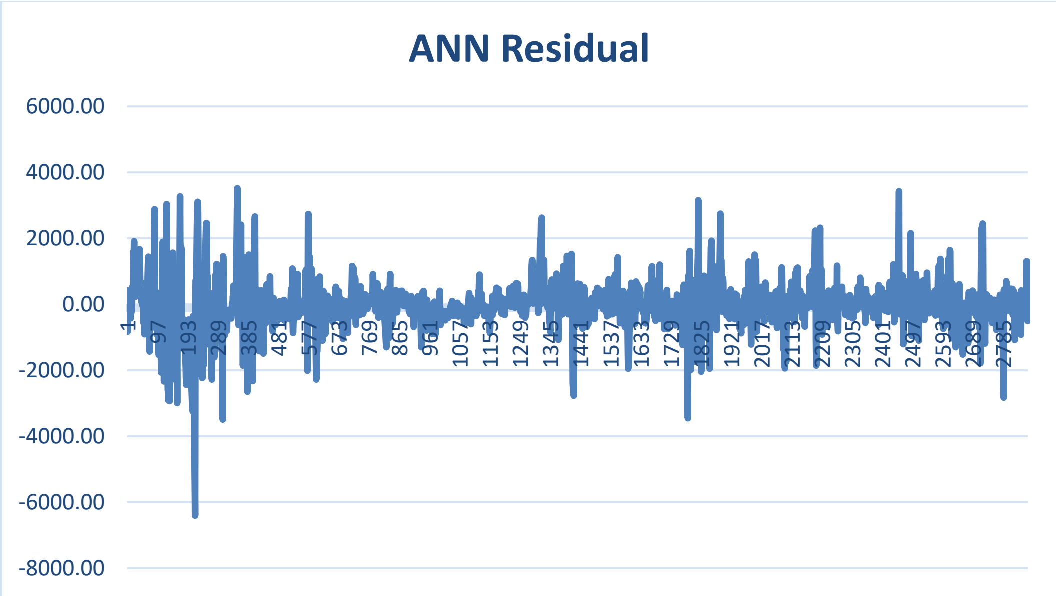

Figure 12: Residuals of the Fitted ANN Model

Using the model estimated in Figure 11 for forecasting, Table 6 below illustrates the prediction of the last ten values of the time series and compares them with the last ten actual values.

Table 6: Forecasting Results of ANN Model

Day	Actual	ANN Forecast
2861	30822.33	30588.39
2862	30704.98	30886.99
2863	30802.9	30669.91
2864	30773.64	30829.83
2865	31967.01	30763.73
2866	31967.01	32353.71
2867	31967.01	31992.25
2868	31692.63	31969.44
2869	31037.72	31603.84
2870	31430.5	30823.55

Comparison Between ARIMA (1,1,2) and ANN Model

Comparison is made between the results obtained from applying both ARIMA and ANN methods through looking at the results and figures that were mentioned previously, in particular figures (4.5), (4.6) and (4.7), as well as tables (4.4), (4.5), (4.6) in addition to the table (4.7) below.

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Table 7: RMSE of ANN and ARIMA Models

	ANN model	ARIMA model
RMSE	0.0047682	0.0135702

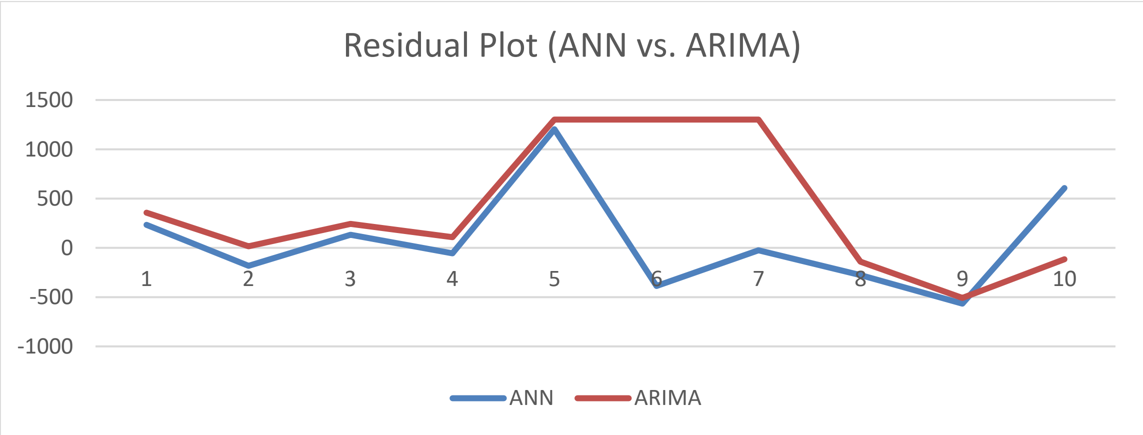

Figure 13: Residuals Plots of ANN and ARIMA (1,1,2)

It can be easily noted from the preceding table that the RMSE of the ARIMA model equivalent to 0.0136 is higher than the RMSE of the ANN model, indicating the efficiency of the ANN model. Thus, we can conclude from the above discussion that the results of the ANN model are much better than the ARIMA model results and more efficient.

SUMMARY OF THE MAJOR FINDINGS

From all the discussion of this study the following could be deduced:

- The ARIMA (1,1,2) model is the best fit for Nigeria's All Share Index among other Box Jenkins models. This was supported by the most of the fit statistic test;
- The ANN model used back propagation algorithm with three units in the hidden layer, two lags and the learning rate equal to 0.1 as the best fit for the Nigeria All Share Index forecasting;
- The use of ARIMA models in forecasting economic and financial data does not give results with high efficiency for more than 3 periods;
- ANN model can be used more effectively in forecasting of stock price index for several points;
- The ANN model performs very well in economic and financial data, and thus it makes a great contribution as an efficient tool for investors to take precaution against potential

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market risks; and

- The ANN model can also be a useful tool to many enterprises, such as commercial companies, banks and insurance companies, that need forecasting stock market indexes in their work.

Conclusion and Recommendation

The empirical results obtained with stock data on the performance of ARIMA and ANN model to stock price prediction of Nigeria's All Share Index have been presented in this study. The performance of the ANN predictive model developed in this study was compared with the conventional Box-Jenkins ARIMA model, which has been widely used for time series forecasting. Our findings revealed that both ARIMA model and ANN model can achieve good forecasts in application to real life problems and thus can be effectively engaged profitably for stock price prediction. We also observed that the pattern of ARIMA forecasting models is directional.

The developed stock price predictive model with ANN-based approach demonstrated superior performance over the ARIMA models; indeed, the actual and predicted values of the developed stock price predictive model are quite close.

Artificial Neural Network (ANN) provides an alternative methodology to ARIMA model for forecasting financial and economic data which has a limited efficiency in this field. So, we recommend taking advantage of the high capacity of artificial neural networks as a forecasting technique in other fields, such as medical research, genetics research, industrial research, energy, and military research. For future work, we suggest conducting a comparison between artificial neural networks and other methods of forecasting, such as the ARCH, GARCH and State Space models, and their applications in economic and financial data.

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