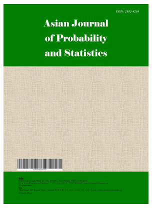

Asian Journal of Probability and Statistics

6(2): 42-53, 2020; Article no.AJPAS.53807

ISSN: 2582-0230

Analysis of ARIMA-Artificial Neural Network Hybrid Model in Forecasting of Stock Market Returns

Yakubu Musa[1*] and Stephen Joshua[1]

[1]Department of Mathematics and Statistics, Usmanu Danfodiyo University, Sokoto, Nigeria.

Authors' contributions

This work was carried out in collaboration between both authors. Authors YM and SJ designed the study, managed the literature searches, wrote the protocol and performed the statistical analysis. Both authors read and approved the final manuscript.

Article Information

DOI: 10.9734/AJPAS/2020/v6i230157

Editor(s):

(1) Dr. Monika Hadas-Dyduch, Lecturer, Department of Mathematical and Statistical Methods in Economics, University of Economics in Katowice, Poland.

Reviewers:

(1) Celil Nebiyev, Ondokuz Mayıs University, Turkey.

(2) A. N. Chavan, Shivaji University, India.

(3) Arya Kumar, Biju Patnaik University of Technology Rourkela Odisha, India.

Complete Peer review History: http://www.sdiarticle4.com/review-history/53807

Received: 04 November 2019
Accepted: 08 January 2020
Published: 24 January 2020

Original Research Article

Abstract

This study focuses on the modelling of Nigerian stock market all–shares index and evaluations of predictions ability using ARIMA, Artificial Neural Network and a hybrid ARIMA-Artificial Neural Network model. The ARIMA (1,1,1) model and neural network with architecture (6:1:3) turns out to be the most fitted among the considered models, these models were used for forecasting the returns, and their performances have been compared according to some statistical measure of accuracy. A hybrid model has been constructed using ARIMA-Artificial Neural Networks model, the computational results on the data reveal that the hybrid model using Artificial Neural Network, provides better forecasts, and will enhance forecasting over the single ARIMA and Artificial Neural Networks models. The study recommends the use of ARIMA-Artificial neural network for modelling and forecasting stock market returns.

Keywords: ARIMA; neural network; hybrid model; forecasting.

**Corresponding author: E-mail: arimaym@gmail.com, ykbmusa@gmail.com;*

1 Introduction

Stock market returns are the returns that the investors generate out of the stock market, this could be in form of profit through trading or in form of dividends given by the company to its shareholders from time to time, stock market returns can be made through dividends announced by the companies. In modern financial time series prediction, predicting stock prices has been regarded as one of the most challenging applications. Thus, various numbers of models have been developed to support investors with more precise predictions. However, stock prices are influenced by a different number of factors and the nonlinear relationships between factors existing in different periods such that predicting the value of stock prices or trends is considered as an extremely difficult task for the investors [1].

There are mainly two approaches of time series modelling and forecasting: Linear approach and non – linear approach. One of the most important and widely used time series models is the autoregressive integrated moving average (ARIMA) model. An ARIMA process combines three different processes comprising an Autoregressive (AR) functions regressed on the past values of the process, Moving Average (MA) functions regressed purely on the random process with mean zero (0) and variance σ^2 and an integrated (I) part to make the data series stationary by differencing. The major limitation of the ARIMA model is the pre-assumed linear form of the model. That is, the linear correlation structure is assumed among the time series values and therefore, no nonlinear patterns can be captured by the ARIMA model. The approximation of linear models to the complex real-world problem is not always satisfactory [2].

In stock market prediction, various numbers of models and theories have been implemented by researchers to improve prediction performance. Some of them use a single linear model, some use a single nonlinear model, others used a hybrid model that combines linear and linear model and some researchers used hybrid model that combines linear and nonlinear model. The study by Ping-Feng and Chih-Shen [3], proposed a hybrid ARIMA and support vector machine (SVM) model to forecasts the stock price of Taiwan stock exchange, real data sets of Taiwan stock prices were used to examine the forecasting accuracy of the proposed model. The result showed great improvement in predictive performance comparable to the prediction of a single SVM model and performance of single ARIMA model in forecasting stock price. Kyungjoo et al. [4], compared the forecasting performance of a neural network (NN) model and a time series (SARIMA) model in the Korean stock exchange. They investigate whether the back-propagation neural network (BPNN) model outperforms the seasonal autoregressive integrated moving average (SARIMA) model in forecasting Korea composite stock price index (KOSPI) and its return. The BPNN model is generally better than the SARIMA model in forecasting the KOSPI returns.

A novel hybrid model was developed by Diaz-Robles et al. [5], combining ARIMA and ANN to improve forecast accuracy for an area with limited air quality and meteorological data was applied to Temuco, Chile, where residential wood burning is a major pollution source during cold winters, using surface meteorological and PM10 measurements. Experimental results indicated that the hybrid model can be an effective tool to improve the PM10 forecasting accuracy obtained by either of the models used separately, and compared with a deterministic multi-linear regression (MLR). The hybrid model was able to capture 100% and 80% of alert and pre-emergency episodes, respectively. This approach demonstrates the potential to be applied to air quality forecasting in other cities and countries.

Akinwale et al. [6], used regression neural network with backpropagation algorithm analyze and predict translated and un-translated Nigerian Stock Market prices (NSMP). Their study compared forecast performance of the neural network with translated and un-translated NSMP as inputs in terms of prediction accuracy measures, the translated NSMP network predicted accurately 11.3% of the stock prices as compared to 2.7% prediction accuracy of the un-translated NSMP network model.

A hybrid methodology that combines both autoregressive integrated moving average (ARIMA) and artificial neural networks (ANNs) was developed by Xiping and Ming [7] to take advantage of the unique strength of ARIMA and ANNs models in linear and nonlinear modeling. The empirical results with energy consumption data of Hebei province China from 2009 to 2013 indicate that the hybrid model can be an effective way to improve the energy consumption forecasting accuracy obtained by either of the models used separately. The result also demonstrates that energy consumption in Hebei province will continue to increase for the next five year. The study by Cagdas et al. [8], proposed a new hybrid approach combining autoregressive fractionally integrated moving average (ARFIMA) and feed-forward neural networks (FNN) to analyse long memory time series. The proposed hybrid method is applied to tourism data of Turkey whose structure shows dominantly the characteristic of long term. Then, this hybrid method is compared with other methods and it is found that the proposed hybrid approach has the best forecasting accuracy. Isenah and Olubusoye [9], compared ARIMA and Artificial Neural network models to forecast Nigerian stock market returns, their study reports empirical evidence that artificial neural network-based models apply to the forecasting of stock market returns. It was found that the artificial neural network-based models outperformed the ARIMA based models in forecasting future developments of the returns process.

Bashar and Maysam [1], proposed a hybrid combination of three models which includes; Support Vector Machine (SVM), Support Vector Regression (SVR) and Back Propagation Neural Network (BPNN). Quantization factor was used to improve the single SVR and SVM prediction output. And also the Genetic Algorithm (GA) was used to determine the weights of the proposed model. FTSE 100, S&P 500 and Nikkei 225 daily index closing prices were used to evaluate the proposed model performance. The proposed hybrid model numerical results outperformed the results of the single model [1]. The study by Suleiman et al. [10], examined the monthly volatility of Naira/Dollar exchange rates in Nigeria between the periods of January 1995 to December 2016. The traditional GARCH and dynamic neural networks were hybridized to develop the proposed model for forecasting volatility of inflation rates in Nigeria. The study applied both symmetric and asymmetric GARCH, the value of the volatility estimated by the best-fitted GARCH as an input to the neural network. The forecasts obtained by each of those hybrid models have been compared with those of GARCH models in terms of the actual volatility. The computational result demonstrates that the second hybrid model provides better volatility forecasts.

The objectives of the study are to building ARIMA model that captures all the linear relationship in the data, studying the neural network approaches to time series and designing Artificial Neural Network for modelling residuals from ARIMA model and hence designing Hybrid model that best enhance forecasting accuracy.

2 Methodology

The focus is to use the autoregressive integrated moving average (ARIMA) techniques based on [11] methodology to build a model and designing Artificial Neural Network for modelling residuals from ARIMA model and hence designing Hybrid model that best enhance forecasting accuracy for the daily Nigerian stock market All –Share- Index, data covers 6 years from 23rd APRIL 2012 to 19th JUNE 2018.

2.1 ARIMA model

An ARIMA (p,d,q) model is a combination of Autoregressive (AR) which shows that there is a relationship between present and past values, random value and a Moving Average (MA) model which shows that the present value has something to do with the past residuals.

The time series {X_t} is said to follow the ARIMA (p,d,q) model if

$$\phi(L)(1-L)^d X_t = c + \theta(L)\varepsilon_t \tag{1}$$

where

$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + ... + \theta_q L^q$$

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \ldots - \phi_p L^p$$

where the ϕ_i, θ_j and $\{ i = 1, \ldots, p$, $j = 1, \ldots, q \}$ are constants such that the zeros of the equations above are all outside the unit circle for stationarity and invertibility respectively.

2.2 The Artificial Neural Network (ANN) approach

When the linear restriction of the model form is relaxed, the possible number of nonlinear structures that can be used to describe and forecasting a time series is enormous. A good nonlinear model should be general enough to capture some of the nonlinear phenomena in the data. Artificial neural networks are one of such models that can approximate various nonlinearities in the data. ANNs are flexible computing frameworks for modelling a broad range of nonlinear problems. One significant advantage of the ANN models over other classes of nonlinear model is that ANNs are universal approximations which can approximate a large class of functions with a high degree of accuracy. Their power comes from the parallel processing of the information from the data. No prior assumption of the model form is required in the model building process. Instead, the network model is largely determined by the characteristics of the data. Single hidden layer feed-forward network will be used in our study. The model is characterized by a network of three layers of simple processing units connected by cyclic links. The relationship between the output (y_t) and the inputs $(y_{t-1}, y_{t-2}, \ldots, y_{t-p})$ has the following mathematical representation:

$$y_t = x_0 + \sum_{j=1}^{q} x_i g\left(\beta_{0j} \sum_{i=1}^{p} \beta_{ij} y_{t-1}\right) + \varepsilon_t \qquad (2)$$

Where $x_j (j = 0,1,2, \ldots, q)$ and $\beta_{ij} (i = 1,2, \ldots, p; j = 1,2, \ldots, q)$ are the model parameters often called the connection weights; p is the number of input nodes and q is the number of hidden nodes. Hence, the ANN model in fact performs a nonlinear functional mapping from the past observations $(y_{t-1}, y_{t-2}, \ldots, y_{t-p})$ to the future value y_t, i.e.,

$$y_t = f(y_{t-1}, y_{t-2}, \ldots, y_{t-p}, w) + \varepsilon_t$$

Where w is a vector of all parameters and f is a function determined by the network structure and connection weights. The choice of q is data-dependent and there is no systematic rule in deciding this parameter.

The estimated model is usually evaluated using a separate hold-out sample that is not exposed to the training process. This practice is different from that in ARIMA model building where one sample is typically used for model identification, estimation and evaluation. The reason lies in the fact that the general (linear) form of the ARIMA model is pre-specified and then the order of the model is estimated from the data. The standard statistical paradigm assumes that under stationary condition, the model best fitted to the historical data is also the optimum model for forecasting. With ANNs, the (nonlinear) model form, as well as the order of the model, must be estimated from the data. It is, therefore, more likely for an ANN model to overfit the data. In our study, we use learning rate 0.4 and momentum 0.9.

2.3 Proposed hybrid method

Both ARIMA and ANN models have achieved successes in their own linear and nonlinear domains. However, none of them is a universal model that is suitable for all circumstances.

Hybrid models have been introduced to overcome the deficiency of using an individual model such as statistical methods (ARIMA, Multiple Regression and e.t.c) and Artificial intelligence (AI) method (fuzzy inference system, genetic algorithms, neural networks, machine learning etc). Hybrid model merges different methods to improve the prediction accuracy. Hybrid models can be referred to as combined models or assemble models. Hybrid methods can be implemented in three different ways, linear models, non-linear model, and both linear and non-linear model.

To tackle these two patterns uniformly well, hybridizing the linear and non-linear patterns is proposed to improve forecasting accuracy. Using Zhang's hybrid methodology [12],

$$Y_t = L_t + N_t \tag{3}$$

Where ARIMA is used as a linear model, L_t and ANN are used as the nonlinear model. N_t, and Y_t denotes the hybrid model that composed of the ARIMA model and nonlinear ANN model. Let e_t denote the residuals at time t from the linear model, then

$$e_t = Y_t - \hat{L}_t \tag{4}$$

Where $\hat{L}_t$ is the forecast value from the estimated relationship of (2). With n input nodes, the ANN model for the residuals will be

$$e_t = f(e_{t-1}, e_{t-2}, \ldots, e_{t-n}) + \varepsilon_t \tag{5}$$

Where f a nonlinear function is determined by the neural network model, and ε_t is the random error. Therefore, the forecast obtained from Hybrid $\hat{Y}_t$ model can be written as

$$\hat{Y}_t = \hat{L}_t + \hat{N}_t \tag{6}$$

Where $\hat{N}_t$ is the forecast values obtained from equation (5) above.

2.4 Performance measures

Three statistical tests would be employed in this study to evaluate the performance of both individual models and hybrid models. These tests utilize error functions such as Root Mean Square Error (RMSE), Mean Error (ME), and Mean Absolute Error (MAE).

Root Mean square errors defined by:

$$\text{RMSE} = \frac{1}{n} = \sqrt{\frac{1}{n}\sum_1^n ei^2} \tag{7}$$

Mean Errors defined by:

$$\text{ME} = \frac{1}{n}\sum_1^n ei \tag{8}$$

Mean absolute error define by:

$$\text{MAE} = \frac{1}{n}\sum_1^n |ei| \tag{9}$$

Where n is the number of observations in the test data set and ei = (A – Â), where A is the actual value and Â is the estimated value.

3 Data Analysis

This section used the Autoregressive Integrated Moving Average (ARIMA) model following Yakubu [13] and Artificial Neural Networks (ANNs) techniques to build a hybrid forecasting model for the Nigerian Stock Market returns using Nigerian stock market all- share- index data set for the period 23rd April 2012 to 19th June 2018.

3.1 Unit root/stationarity test

To investigate the order of integration of a time series, a unit root/Stationarity tests were conducted. The DF(GLS) test checks the null hypothesis of unit roots against the alternative that the series is stationary. The results for the unit root test are presented in Table 1.

Table 1. Tests of the data before differencing

Test	t- statistics	p-value
ADF(GLS)	-0.7781	0.3794
KPSS	0.8951	< 0.01

At 5% level, the ADF(GLS) test accept the null hypothesis of the unit root test and KPSS rejects the null hypothesis. After first differencing, the series is now stationary.

Table 2. Tests of the data after differencing

Test	t- statistics	p-values
ADF(GLS)	-14.5983	2.848e-31
KPSS	0.030457	> .10

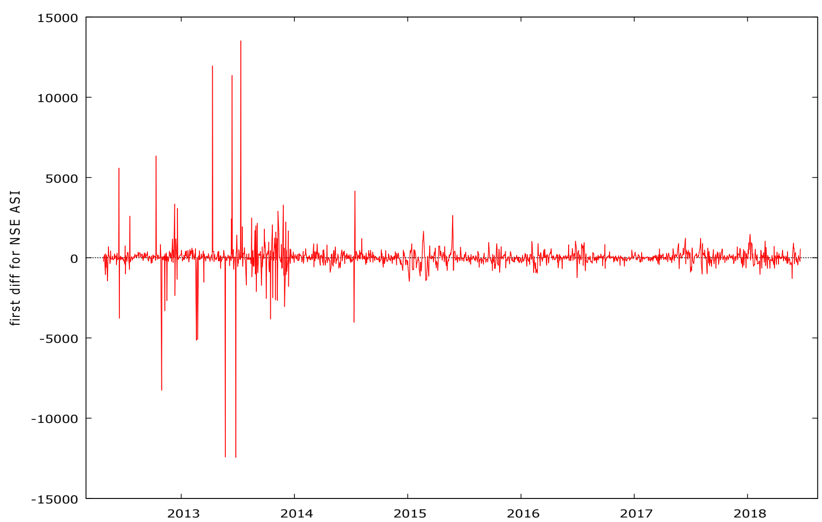

Fig. 1. Time plot of differenced data

3.2 Model identification using information criteria

Using Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn Information Criterion (HIC), ARIMA(1,1,1) were found to be the best model that have minimum values for the different criteria used.

3.3 Diagnostic checking

Two test statistics was conducted for all the models using the Ljung-Box test and ARCH-LM tests. The following results were obtained;

Table 3. Autocorrelation tests for the residuals

	Ljung-Box test	
	Test statistic	**p-value (chi-square)**
ARIMA (1,1,1)	19.6275	0.0118
	ARCH-LM test	
	Test statistics	**p-value (chi-square)**
ARIMA (1,1,1)	38.6539	2.9186e-0.05

The two different tests that have been conducted are to check for the adequacy of the model.

We found out that p-value in all the cases is less than the test statistic; hence the model is adequate to fit the data.

3.4 Models forecast

Having known from the results obtained from information criteria that ARIMA (1,1,1) is the model with the least information criteria, the following results were obtained for thirty days-step-ahead out-of-sample forecasts.

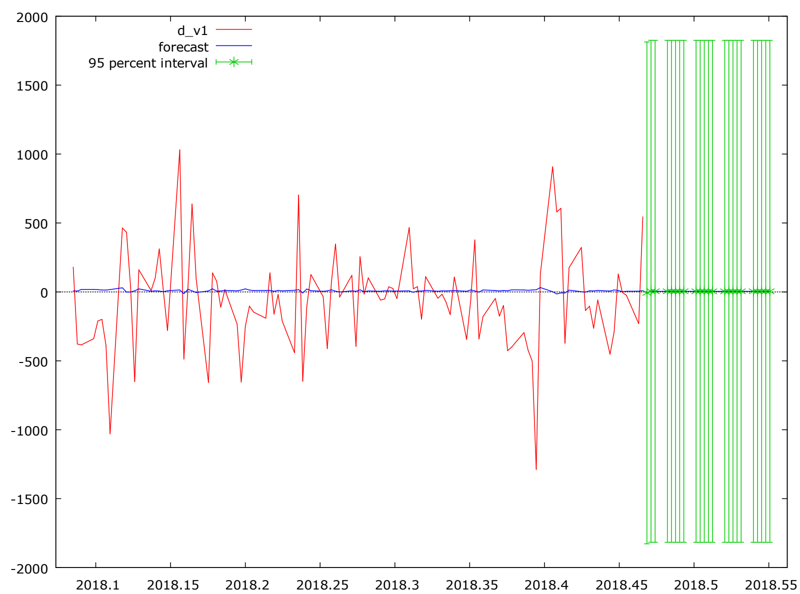

Fig. 2. ARIMA (1,1,1) prediction for NSM all share index, at 95% interval

ARIMA (1,1,1) model forecast, show continuous steady fluctuations returns for a whole month.

Table 4. Performance measure

Model	**RMSE**	**MAE**	**MAPE**
ARIMA(1,1,1)	931.1	348.14	119.56

3.5 Artificial Neural Networks (ANNs)

The results obtained from the artificial neural network were presented. The different number of network architecture were tried ranging from one to sixteen to select the best one in terms of the predicted values, six networks with different architecture were selected to be the best out of the sixteen network architectures, normally the one with smaller RMSE, MAE and MAPE values is selected. The number of the hidden layer is fixed to be one throughout the training. The number of the hidden layer is fixed to be one throughout the training. During the training, some parameters were also set as constants which include the boundary of initial learning rate which is 0.5, maximum epochs of training 1000, the lower boundary of learning rate is 0.002, and momentum of 0.8. The algorithm used for the training is Scaled Conjugate Gradient (SCG) algorithm.

Matlab R2018a was used for the neural network analysis.

Training Neural Network Architecture: Training neural network architecture is very simple but time-consuming because the Matlab has been program and provided with different training algorithms, performance measures, activation functions and so on. The needs for adjusting the network parameters until a good network is obtained are required, after so many iterations, comparisons are then made using the mean squared errors or any desired performance measures. The network with the minimum mean square error is considered to be the best among the networks.

In training our network the sample was divided into three portions, we use 50% for training, 25% for testing and 25% for holdout or validations. The different number of network architecture were tried ranging from one to sixteen to select the best one in terms of the predicted values, six networks with different architecture were selected to be the best out of the sixteen network architectures, normally the one with smaller RMSE, MAE and MAPE values is selected. The number of the hidden layer is fixed to be one throughout the training. During the training, some parameters were also set as constants which include the boundary of initial learning rate which is 0.5, maximum epochs of training 1000, the lower boundary of learning rate is 0.002, and momentum of 0.8. The algorithm used for the training is Scaled Conjugate Gradient (SCG) algorithm. Different networks with different numbers of hidden neurons and delays were trained and their performance results are shown in Table 5.

Table 5. Performance results for different network architectures

Network structure	RMSE	MAE	MAPE
NN(6:1:2)	21.2577	0.8794	344.244
NN(7:1:7)	21.2665	0.8902	364.443
NN(6:1:3)	**21.2016**	**0.7854**	**148.394**
NN(7:1:3)	21.2727	0.8989	419.333
NN(8:1:2)	21.2587	0.8846	347.784
NN(6:1:1)	21.4563	0.9865	352.455

The smaller the values of MSE, MAE and MAPE the better the forecast performances. From Table 5 the values of MSE, MAPE and MAE are the least when the number of neuron in the hidden layer is 6 with 3 delays, thus neural network with architecture (6:1:3) is the best network among the trained models, the performance plot and Regression plot for the selected network is shown in Fig. 3 and Fig. 4 respectively.

In Fig. 3, the blue line shows the decreasing error on a training data, the green line shows the validation error and the red line shows the error on the test data indicating how well the network will generalize the new data. The best validation performance occurs at 257 epoch, the training stops when the validation error stops decreasing as we can see in the figure after epoch 257 the lines stop decreasing.

The regression plot in Fig. 4 is the plot that is also used to validate the network performance, it displays the network outputs concerning targets for training, validation and test sets. For a perfect fit, the data must fall along a 45-degree line, where the network outputs are equal to the target. For our work, all the line fall in 45 degrees this shows that the fit is reasonably good for all data sets.

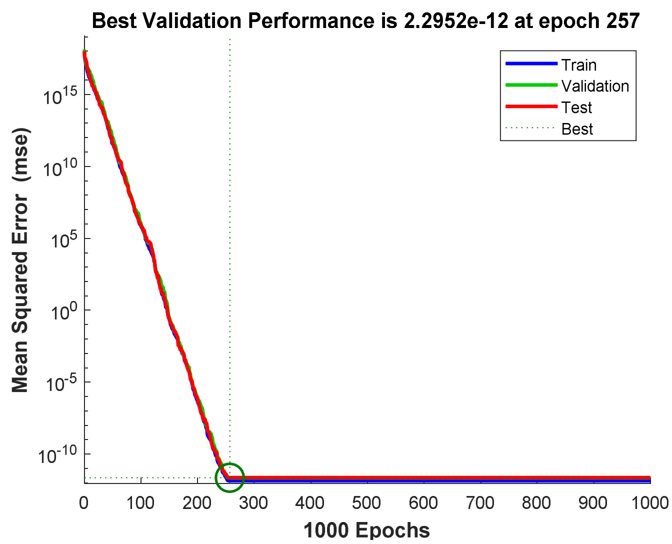

Fig. 3. Plot performance for network architecture 6:3:1

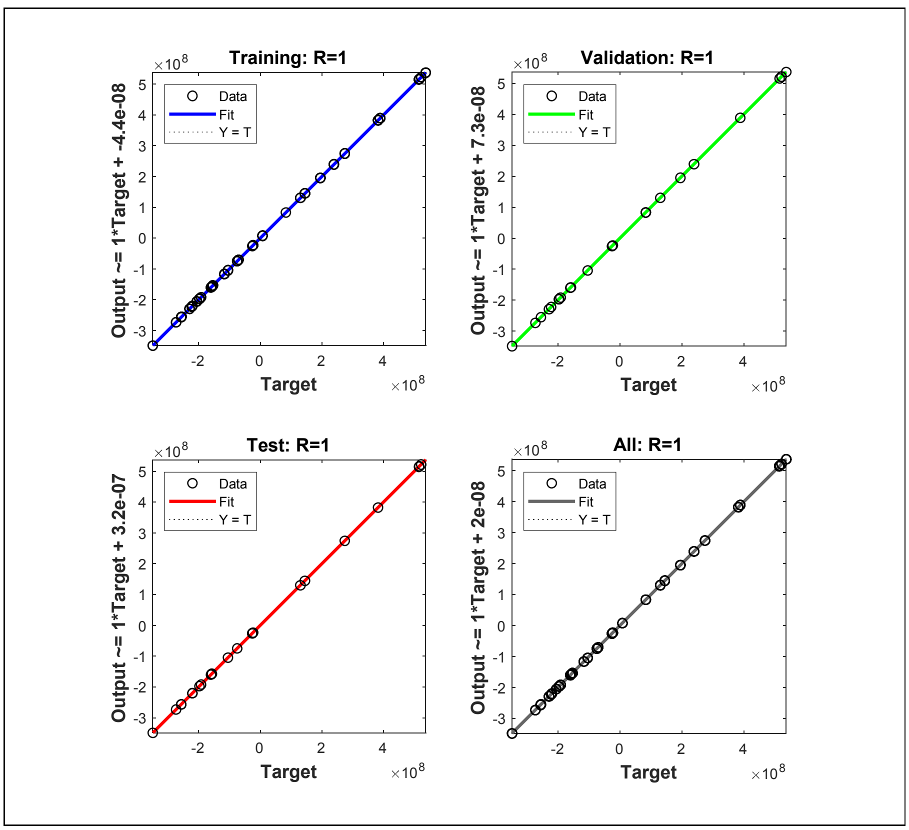

Fig. 4. Regression plot for network architecture 6:1:3

3.6 Hybrid implementation

With the procedures, analysis and results obtained from ARIMA modelling and building a neural network model, building a forecasting hybrid model are straight forward since the hybrid model will be built using the best trained selected neural network model.

Matlab also was used in building a hybrid model using residual series that ARIMA(1,1,1) was unable to model. Having known the best performed neural network to be NN(6:1:3). The residuals from the ARIMA model is presented to Neural network which gives the Hybrid ARIMA Neural Network model. The Figures below shows the performance of the hybrid model.

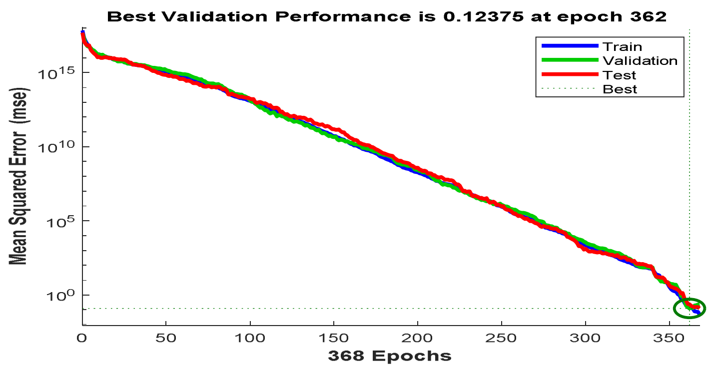

Fig. 5. Plot performance for the hybrid model

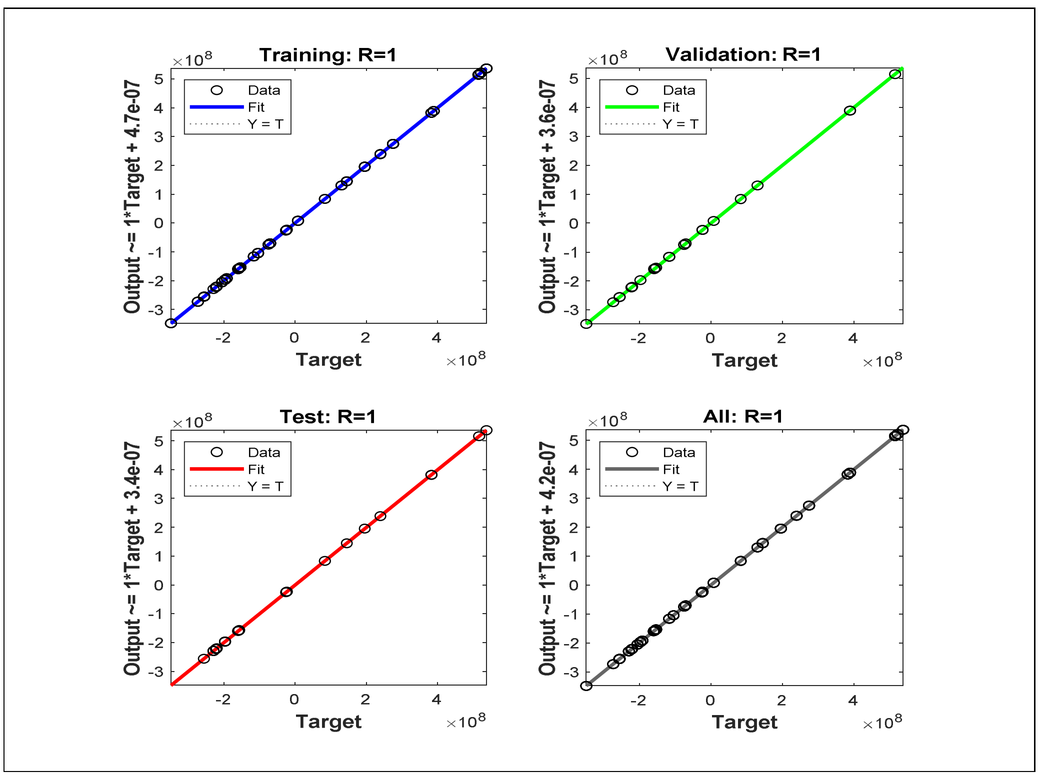

Fig. 6. Regression plot for hybrid

In Fig. 5, the blue line shows the decreasing error on a training data, the green line shows the validation error and the red line shows the error on the test data indicating how well the network will generalize the new data. The best validation performance occurs at 362 epoch, the training stops when the validation error stops decreasing as we can see in the figure after epoch 362 the lines stop decreasing. The regression plot in Fig. 6 also falls along a 45-degree line, where the network outputs are equal to the target which shows that the fit is reasonably good for all data sets.

Table 6. Hybrid model forecast performance results

Model	MSE	MAE	MAPE
Hybrid	20.1237	0.6443	98.122

3.7 Comparison of model performance for NSM all-share-index

To examine the fitness of the ARIMA model, Artificial Neural Network and the Hybrid model, all the models have been used to make out of sample forecast and their performance errors results are reported and summarized in Table 7.

Table 7. Forecast performance comparison for ARIMA, neural network and hybrid models

Model	RMSE	MAE	MAPE
ARIMA (1,1,1)	931.1	348.14	119.56
NN(6:1:3)	21.2016	0.7854	148.394
HYBRID	20.1237	0.6443	98.122

4 Conclusion

The study investigated the performance of the ARIMA model, neural network model and the Hybrid ARIMA Neural network model to the Nigerian stock market returns. The linear ARIMA model and nonlinear ANN model are used jointly which result in the Hybrid model, aiming to capture different forms of relationships in the time series. From the results obtained in the study, we found that with NSM all-share-index, the best linear ARIMA model is ARIMA (1,1,1), and neural network with structure (6:1:3) is used to model the nonlinear patterns in the data. Table 7 shows that the hybrid model performed better than both ARIMA and Neural Network in their single domain indicating their suitability for financial time series forecasting. In terms of RMSE, MAE and MAPE, the computational results on the data demonstrate that the hybrid model using artificial neural networks provides better forecasts, followed by Artificial Neural Network in its single domain. Thus, this hybrid model enhances forecasting over the ARIMA and ANN Model.

Competing Interests

Authors have declared that no competing interests exist.

References

[1] Bashar A, Maysam A. Predicting financial time series data using hybrid model. Intelligent Systems and Applications. 2016;10:19-41.

[2] Norizan M, Maizah HA. Forecasting Malaysia load using hybrid model. Statistika. 2010;10:1-8.

[3] Ping-Feng P, Chih-Shen L. A hybrid ARIMA and support vector machine model in stock price forecasting. International Journal of Management Science. 2005;33:497-505.

[4] Kyungjoo L, Schwan Y, John JJ. Neural network model vs SARIMA model in forecasting Korean stock market index. Issues in Information System. 2007;2:372-378.

[5] Diaz-Robles LA, Juan C. Ortega, Joshua SF. A hybrid ARIMA and artificial neural networks model to forecast particulate matter in urban areas; The case of Temuco, Chile. Journal Atmospheric Environment. 2008;42:8331-8340.

[6] Akinwale A, Arogundade OT, Adekoya AF. Translated Nigeria stock market prices using artificial neural network for effective prediction. Journal of Theoretical and Applied Information Technology. 2009;2:36-43.

[7] Xiping W, Ming M. A hybrid neural network and ARIMA model for energy consumption forecasting. Journal of Computers. 2012;7:1184-1190.

[8] Cagdas H, Erol E, Cem K. Improvement in forecasting accuracy using the hybrid model of ARFIMA and feed forward neural network. American Journal of Intelligent Systems. 2012;2:12-17.

[9] Isenah GM, Olubusoye EO. Forecasting Nigerian stock market returns using ARIMA and artificial neural network model. CBN Journal of Applied Statistics. 2014;5:25-48.

[10] Suleiman S, Gulumbe SU, Asare BK, Abubakar M. Training dynamic neural networks for forecasting Naira/Dollar Exchange return volatility in Nigeria. American Journal of Management Science and Engineering. 2016;1(1):8-14.

[11] Box GE, Jenkins. Time series analysis forecasting and controls. San Francisco. USA; 1974.

[12] Zhang GP. Times series forecasting using a hybrid ARIMA and neural network model. Neurocomputing. 2003;50:159–175.

[13] Yakubu Musa. Modeling monthly average temperature of Sokoto metropolis using short term memory models. International Journal of Academic Research in Business and Social Sciences. 2014;4(7):382-397.

Peer-review history:
The peer review history for this paper can be accessed here (Please copy paste the total link in your browser address bar)
http://www.sdiarticle4.com/review-history/53807