A Hybrid Factor Based Neural Network Model Application for Stock Price Prediction

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Abstract - **This paper demonstrates the use of neural network error back propagation algorithm in analyzing and predicting of Nigeria Stock Market Prices. Nigeria stock market prices were collected for the period of one thousand, two hundred and three days and subjected into training, validation and testing. A zero mean unit variance transformation was used to normalize the input variables in order to allow the same range which makes them to differ by order of magnitude. A 14-*j*-1 network topology was adopted because of fourteen input variables in which variable *j* was determined by the number of hidden neurons during network selection. The technical and fundamental data served as input into the error back propagation algorithm which was simulated with MATLAB and implemented with Java programming language. From the results obtained, Nestle Nigerian Plc. recorded a mean squared error (MSE) and regression (R) values of 466186e-6 and 0.999923 respectively, Guinness Nigerian Plc. recorded a mean squared error (MSE) and regression (R) values of 8.29839e-7 and 0.999873 respectively and Total Nigerian Plc. recorded a mean squared error (MSE) and regression (R) values of 3.07993e-6 and 0.999193 respectively. The result shows that using hybridize factors input variables gives a better result in stock market prediction with minimum amount of error.**

Keywords: ***Neural network, regression value, mean square, technical analysis and fundamental analysis.***

I. INTRODUCTION

Prediction in stock market has been a hot research area for many years [6]. If any system which can consistently predict the trends of the dynamic stock market be developed, it would make the owner of the system wealthy. Many investments professionals and market participants have met the efficient market hypothesis with skepticism and regard it purely as conservative academic opinion. They believed that mechanism can be devised to predict market prices. The characteristic that all stock markets have in common is the uncertainty, imprecision which is related with their short and long-term future state. The purpose of prediction is to reduce uncertainty associated to investment decision making. [11]. This feature is undesirable for the investor but it is also unavoidable whenever the stock market is selected as the investment tool. Stock market follows a random walk, which implies that the best prediction you can have about tomorrow's value is today's value. Indisputably, forecasting stock indices is very difficult because of the market volatility that needs accurate forecast model. The stock market indices are highly fluctuating and it affects the investor's belief. Determining more effective ways of stock market index prediction is important for stock market investors in order to make more informed and accurate investment decisions. Many studies on stock market prediction using Artificial Neural Networks or statistical methods were performed on technical raw data. These data might have been affected by inflation or fluctuation of exchange rates especially in developed countries such as Nigeria [2].

Back propagation neural network is commonly used for price prediction [14]. The objective of this paper is to demonstrate the use of neural network back propagation learning algorithm in training and simulating stock market data using hybrid factor variables as inputs to generate the optimal prediction.

II. LITERATURE REVIEWS

Predicting the stock market is very difficult since it depends on several known and unknown factors. So many methods like technical analysis, fundamental analysis, time series analysis and statistical analysis have been used in attempting to predict the price in the stock market, but none of these methods are proved as a consistently acceptable prediction tool. This paper will not be complete without mentioning researches done by scholar in this area; Kyoung-jae proposes genetic algorithms (GAs) approach to feature discrimination and the determination of connection weights for artificial neural networks (ANNs) to predict the stock price index. In their study, GA is employed not only to improve the learning algorithm, but also to reduce the complexity in feature space. Experiment results show that GA approach to the feature discrimination model outperform the other two conventional models. [4]

Qing et al. in their study used artificial neural networks to predict stock price movement (i.e., price returns) for firms traded on the Shanghai stock exchange. We compare the predictive power using linear models from financial forecasting literature to the predictive power of the univariate and multivariate neural network models. Our results show that neural networks outperform the linear models compared. These results are statistically significant across our sample firms, and indicate neural networks are a useful tool for stock price prediction in emerging markets, like China. [8]

Yi-Hsien, in his study integrated new hybrid asymmetric volatility approach into artificial neural networks option-pricing model to improve forecasting ability of derivative securities price. Owing to combines the new hybrid asymmetric volatility method can be reduced the stochastic and nonlinearity of the error term sequence and captured the asymmetric volatility simultaneously. Hence, in the ANNS option-pricing model, the results demonstrate that Grey-GJR– GARCH volatility provides higher predictability than other volatility approaches. [12]

Pei-Chan et al. in their study, an integrated system, CBDWNN by combining dynamic time windows, case based reasoning (CBR), and neural network for stock trading prediction is developed and it includes three different stages, beginning with screening out potential stocks and the important influential factors; and using back propagation network (BPN) to predict the buy/sell points (wave peak and wave trough) of stock price and adopting case based dynamic window (CBDW) to further improve the forecasting results from BPN. The empirical results show that the CBDW can assist the BPN to reduce the false alarm of buying or selling decisions.[7]

Sheng-Hsun et al., in their study employs two-stage architecture for better stock price prediction. Specifically, the self-organizing map (SOM) was first used to decompose the whole input space into regions where data points with similar statistical distributions are grouped together, so as to contain and capture the non-stationary property of financial series. After decomposing heterogeneous data points into several homogenous regions, support vector regression (SVR) is applied to forecast financial indices. The proposed technique was empirically tested using stock price series from seven major financial markets. The results show that the performance of stock price prediction can be significantly enhanced by using the two-stage architecture in comparison with a single SVR model. [11]

Zhang in their paper proposed an improved bacterial chemo taxis optimization (IBCO), which is then integrated into the back propagation (BP) artificial neural network to develop an efficient forecasting model for prediction of various stock indices. Experiments show its better performance than other methods in learning ability and generalization. [13]

Akinwale examined the use of error back propagation and regression analysis to predict the untranslated and translated Nigeria Stock Market Price (NSMP). The author was used 5 -j -1 network topology to adopt the five input variables. The number of hidden neurons determined the variables during the network selection. Both the untranslated and translated statements were analyzed and compared. The Performance of translated NSMP using regression analysis or error propagation was more superior to untranslated NSMP. The result was showed on untranslated NSMP ranged for 11.3% while 2.7% for NSMP. [2]

Haven examined other scholars work; this research looks at a hybrid factor based Neural Network model application for Stock Price Prediction. In this research important fundamental and technical factors that affect stock market will form the input for the Neural Network. This fundamental factor includes the gross domestic product and inflation rate and then the technical factor includes the close price, opening price, lowest price, the highest price and the volume.

III. MATERIALS AND METHODS

For the purpose of training our data, the back propagation algorithm was used, we obtained data from the daily index values of the Nigerian stock exchange (NSE) for three selected companies. The selected companies include Total Nigeria Plc., Nestle Nigeria Plc. and Guinness Nigeria Plc. The data were collected from January 2008 to march 2013. The source of data used is www.cashcraft.com which provides daily stock market data reports of these companies. The system requirement includes the system input variables which comprises of both the technical and the fundamental input variables. [1] The technical and the fundamental input variables are listed as

O*i-1* the opening price of day *i-1*
O*i-2* the opening price of day *i-2*
H*i-1* the daily high price of day *i-1*
H*i-2* the daily high price of day *i-2*
L*i-1* the daily low price of day *i-1*
L*i-2* the daily low price of day *i-2*
C*i-1* the closing price of day *i-1*
C*i-1* the closing price of day *i-2*
V*i-1* the trading volume of day *i-1*
V*i-2* the trading volume of day *i-2*
G*i-1* thegross domestic product of year *i-1*
G*i-2* thegross domestic product of year *i-2*
I*i-1* the inflation rate of year *i-1*
I*i-2* the inflation rate of year *i-2*

We have a total of 14 input variables, these inputs were normalized which is an appropriate stage in training the data obtained using neural networks applications that was developed. The input data is normalized into the range of [0, 1] or [-1, 1] according to the activation function of the neurons. [5]. In this paper the value of the stock market is normalized into the range of [0, 1] using a sigmoid function and the neural networks are trained and tested using the back propagation algorithm.

A. *The Architectural Model of the Proposed System*

The architecture of this model consists of a 14-*j*-*1*network topology because of fourteen input variables in which variable *j* was determined by the number of hidden neurons during network selection. Figure: 3.1 depicts a schematic diagram of a 14-3-1 topology and fourteen input variableare: $X1_1$, $X1_2$, $X1_3$,...$X1_{14}$. This is the combination of both technical and fundamental variables. The hidden layer of $X2_1$, $X2_2$, and $X2_3$ are intermediate variables which interact by means of weight matrices with adjustable weights to produce the output.

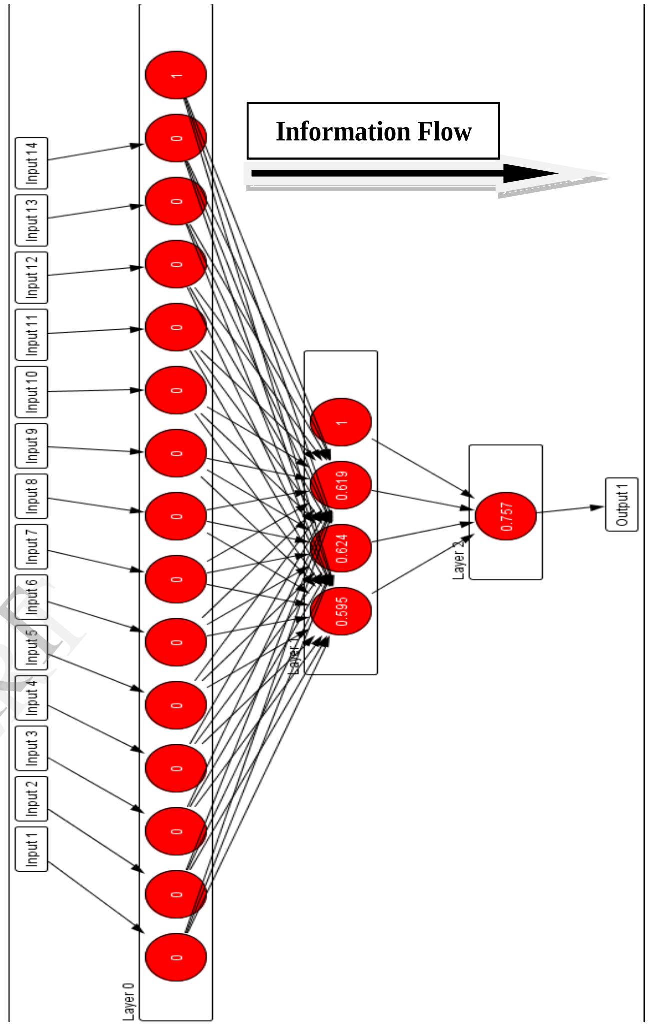

Fig: 3.1: Neural Network Model Architecture of the System

Forward propagation is a supervised learning algorithm and describes the "flow of information" through a neural net from its input layer to its output layer.[3] The feed forward algorithm was used to calculate the optimal weights of the stock prediction. The mathematical models for the feed forward algorithm are as follows:

$$\boldsymbol{Input_j} = \boldsymbol{x_j} = \sum y_i w_{ij} \qquad 3.1$$

y_i is the generated output and w_{ij} represents weights

$$f(x) = \frac{1}{1+e^{-x_j}} \qquad 3.2$$

f (x) is a sigmoid that is used as the activation function

$$Error = T_k - O_k \qquad 3.3$$

T_k is the observed (True) output while Ok is the calculated (actual) output

The error in the output layer is calculated by using the formula in equation 3.4

$$\delta_k = o_k(\mathbf{1} - \boldsymbol{o}_k)(\boldsymbol{T}_k - o_k) \qquad 3.4$$

Where O_k is the calculated (actual) output expressed in equation 3.5

$$O_k = \frac{1}{1+e^{-x_k}} \qquad 3.5$$

T_k is the observed (True) output

The back propagation error in the hidden layer is calculated by using the formula in equation 3.6

$$\delta_j = o_j(\mathbf{1} - \boldsymbol{o}_j)\sum_{\boldsymbol{k}} \delta_k * w_{jk} \qquad 3.6$$

Where w_{jk} is the weight of the connection from unit j to unit k in the next layer and δ_k is the error of unit k.

The weight adjustment formula in equation (3.7) is used to adjust the weights to produce new weights which are fed back into the input layer.

$$\boldsymbol{W_{new}} = \boldsymbol{W_{old}} + \boldsymbol{\eta * \delta * input} \qquad 3.7$$

Where η is a constant called the learning rate. The learning rate takes value between 0 and 1.

IV. EXPERIMENTS AND RESULTS

The simulation was done using Matlab. Figure 4.1 shows the Neural Network fitting tool for data selection. This Interface helps in collection of input data and the target data from the work space.

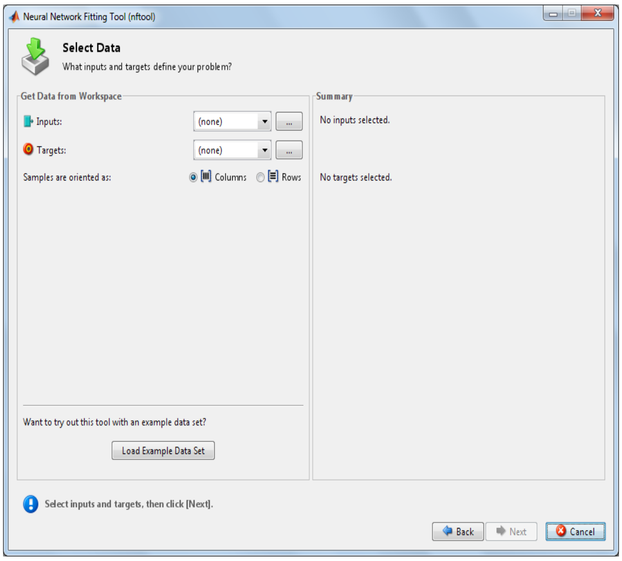

Fig 4.1 Neural Network Fitting Tool for Data Selection

Figure 4.2 shows the Neural Network fitting tool for selection of network size. This interface gives the user the opportunity to select the number of neuron in the network's hidden layer. The user can return to this panel and change the number of the neuron if the network does not perform well after training.

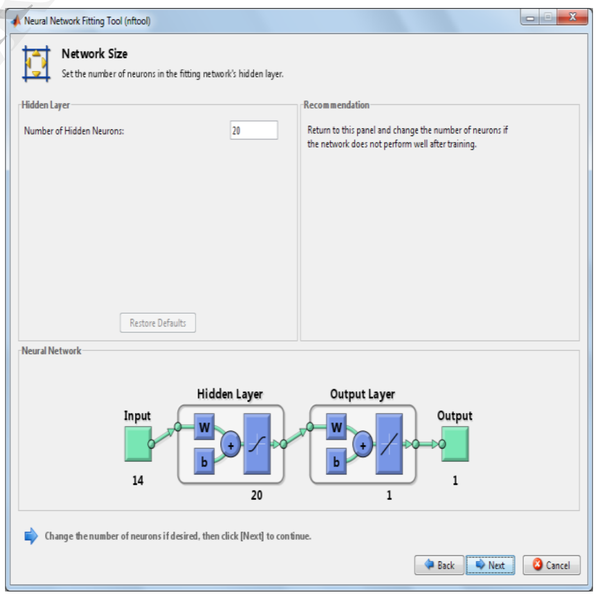

Fig 4.2 Neural Network Fitting Tool for Network Size Selection

Figure 4.3 shows the Neural Network training. The Neural Network model was trained using Levenberg-Marquardt back propagation. The network is trained to fit the inputs and the target. This means that neural network map between a data of numeric inputs and a set of numeric targets. Training automatically stops when generalization stops improving as indicated by the increase in the mean square error of the validation samples.

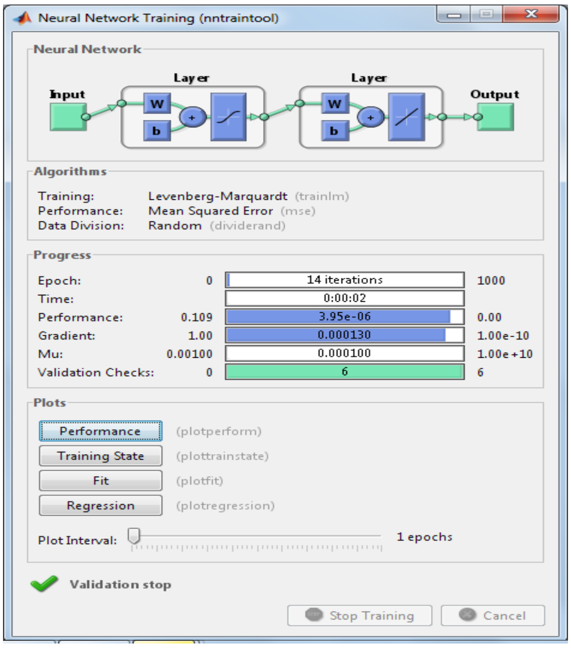

Fig 4.3 Neural Network Training Tool

The neural network fitting tool will help in training network and evaluation its performance using mean square error and regression analysis. Training multiple times will generate different results due to different initial condition and sampling. Figure 4.4 shows the result of the trained Network.

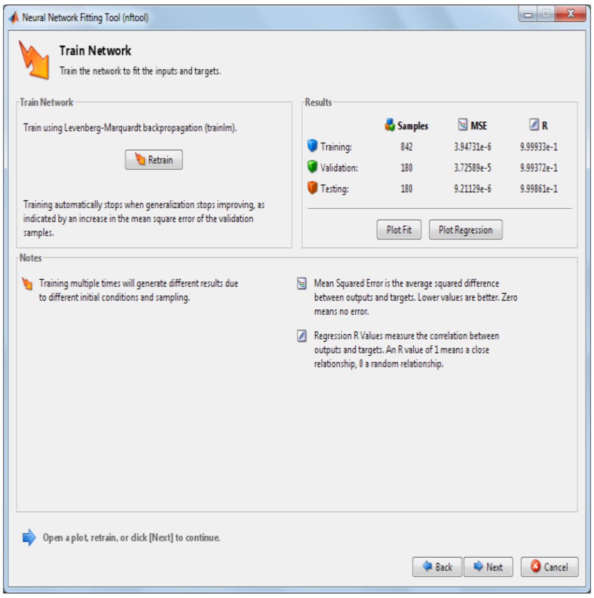

Fig 4.4 Neural Network Fitting Tool for Displaying the Result of the Trained Network.

Table: 4.1. The Performance Analysis of the Nestle Nigerian Plc. Prediction

	No of Samples	*Mean Squared Error (MSE)*	Regression (R) Values
Training	842	4.66186e-6	0.999923
Validation	180	3.25520e-5	0.999466
Testing	180	4.25777e-5	0.99244

Table: 4.2 the Performance Analysis of the Total Nigerian Plc. Prediction

	No of Samples	Mean Squared Error (MSE)	Regression (R) Values
Training	842	3.07993e-6	0.999193
Validation	180	4.91378e-6	0.998718
Testing	180	8.15871e-6	0.998029

Table: 4.3 The Performance Analysis of the Guinness Nigerian Plc. Prediction

	No of Samples	Mean Squared Error (MSE)	Regression (R) Values
Training	841	8.29839e-7	0.999873
Validation	180	1.07882e-6	0.999852
Testing	180	2.44880e-6	0.999690

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Table: 4.4 Stock Predictions for Nestle Nigerian Plc.

Sample of Daily Stock Price Prediction for Nestle Nigerian Plc.									
Sample Date	**Actual value**	**Predicted Values with Different Neural Network Predictive Models**							
		14-21-1	14-20-1	**14-19-1**	14-18-1	14-17-1	14-16-1	14-15-1	14-14-1
20/3/2013	**834.00**	835.01	834.50	**834.48**	843.66	835.28	834.76	840.82	830.89
21/3/2013	**870.00**	864.64	861.95	**861.99**	861.87	863.36	866.46	860.40	864.96
22/3/2013	**860.00**	863.87	861.01	**861.65**	861.57	863.11	862.69	861.55	864.90
25/3/2013	**860.00**	861.84	861.98	**863.91**	866.07	859.55	865.94	864.45	862.21
26/3/2013	**916.00**	912.00	911.46	**914.42**	916.25	913.44	915.46	910.74	911.56
27/3/2013	**940.00**	946.30	941.92	**941.39**	940.76	945.55	952.76	944.13	945.24
28/3/2013	**950.00**	945.23	946.31	**949.01**	949.11	949.46	947.80	950.35	951.12
2/4/2013	**960.02**	957.74	956.99	**957.39**	957.82	957.16	958.59	957.61	958.12
3/4/2013	**960.11**	960.05	958.62	**958.56**	956.00	958.42	959.09	960.04	959.91
4/4/2013	**960.15**	959.93	958.40	**959.13**	959.54	956.73	959.06	957.90	959.15
5/4/2013	**960.50**	961.13	960.75	**961.33**	961.89	959.15	961.81	960.65	961.17
8/4/2013	**970.00**	969.12	968.77	**969.51**	970.38	967.88	969.38	968.21	969.39
9/4/2013	**973.00**	971.28	970.76	**970.48**	971.03	970.02	970.93	970.68	971.90
10/4/2013	**972.00**	971.70	970.67	**970.61**	971.02	969.25	971.01	970.38	971.65

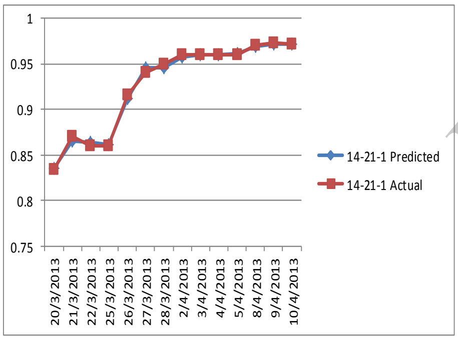

Fig 4.5 Graph of 14-21-1Predictive model.

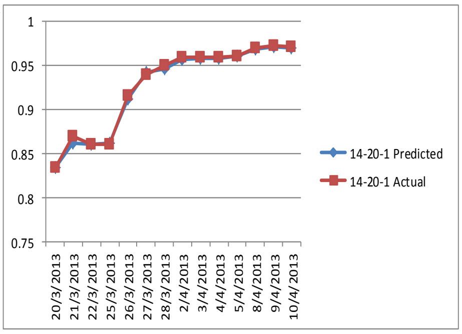

Fig 4.6 Graph of 14-20-1Predictive model.

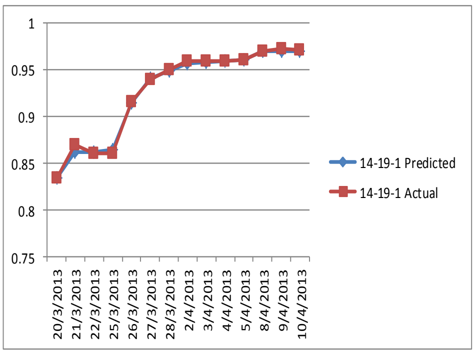

Fig 4.7 Graph of 14-19-1Predictive model.

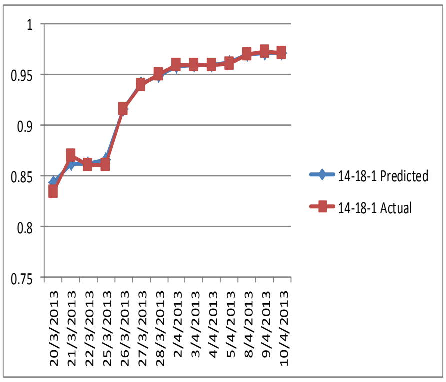

Fig 4.8 Graph of 14-18-1Predictive model.

Table: 4.5 Stock Predictions for Total Nigerian Plc.

Sample of Daily Stock Price prediction for Total Nigerian Plc.									
Sample Date	**Actual value**	**Predicted Values with Different Neural Network Predictive Models**							
		14-21-1	**14-20-1**	14-19-1	14-18-1	14-17-1	14-16-1	14-15-1	14-14-1
20/3/2013	**161.00**	160.70	**161.03**	161.5	161.18	161.15	161.26	161.48	161.30
21/3/2013	**161.00**	160.65	**161.05**	161.41	161.13	161.18	161.28	161.49	161.30
22/3/2013	**161.00**	160.66	**161.05**	161.36	161.11	161.17	161.29	161.48	161.25
25/3/2013	**161.00**	160.66	**161.05**	161.36	161.11	161.17	161.29	161.48	161.25
26/3/2013	**161.00**	160.00	**160.77**	161.57	161.69	161.12	160.26	161.19	160.86
27/3/2013	**161.00**	161.42	**160.58**	161.37	161.88	161.15	161.24	162.46	161.90
28/3/2013	**169.05**	169.59	**169.49**	167.82	169.57	169.38	170.11	170.37	170.60
2/4/2013	**180.00**	178.16	**180.19**	180.14	180.88	179.80	179.69	178.69	180.39
3/4/2013	**180.00**	180.48	**180.33**	180.41	179.73	180.16	180.30	179.26	180.46
4/4/2013	**180.00**	180.19	**180.45**	180.09	179.72	179.86	179.59	180.16	179.96
5/4/2013	**180.00**	180.14	**180.46**	179.94	179.67	179.84	179.65	180.13	179.95
8/4/2013	**180.00**	180.30	**180.41**	180.05	179.78	179.88	179.62	180.21	179.97
9/4/2013	**180.00**	180.32	**180.41**	180.26	179.84	179.84	179.54	180.23	179.98
10/4/2013	**180.00**	179.55	**180.67**	179.47	179.18	179.99	179.82	179.82	179.88

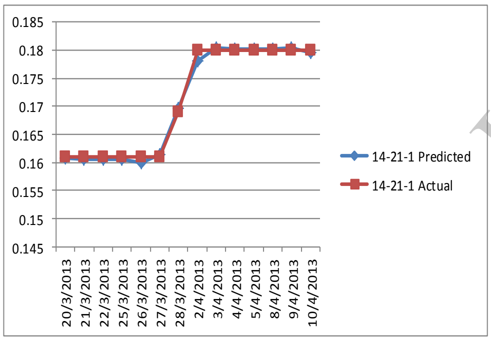

Fig 4.9 Graph of 14-21-1Predictive model.

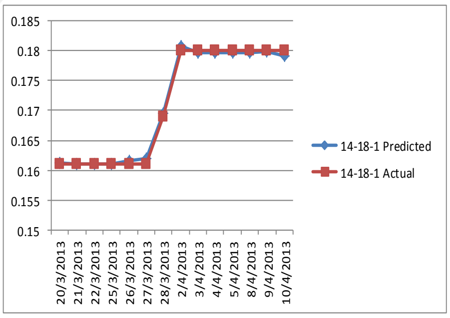

Fig 4.10 Graph of 14-18-1Predictive model.

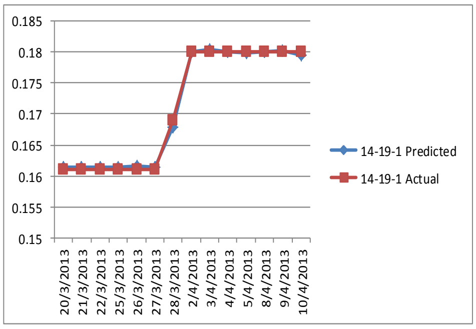

Fig 4.11 Graph of 14-19-1Predictive model.

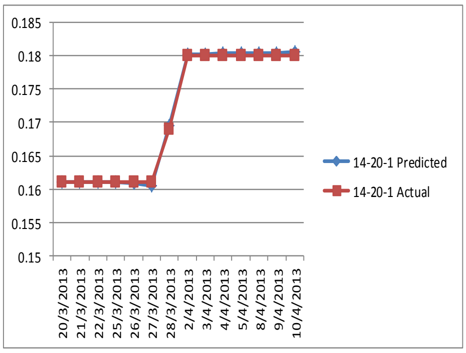

Fig 4.12 Graph of 14-20-1Predictive model.

Table:4.6 Stock Predictions for Guinness Nigeria Plc.

Sample of Daily Stock Price prediction for Guinness Nigeria Plc.									
Sample Date	**Actual value**	**Predicted Values with Different Neural Network Predictive Models**							
		14-21-1	14-20-1	14-19-1	14-18-1	**14-17-1**	14-16-1	14-15-1	14-14-1
20/3/2013	**265.00**	265.25	264.92	265.43	265.07	**265.07**	265.35	265.52	265.24
21/3/2013	**267.00**	267.13	266.86	267.45	266.94	**266.96**	267.23	267.22	267.29
22/3/2013	**265.00**	264.88	264.79	264.99	264.65	**264.95**	265.03	265.28	264.62
25/3/2013	**265.00**	265.25	265.03	265.64	265.04	**264.99**	265.01	265.21	265.23
26/3/2013	**263.01**	262.64	262.68	263.07	262.64	**262.79**	262.90	263.33	262.50
27/3/2013	**263.80**	263.84	263.84	264.27	263.78	**263.74**	263.75	264.09	263.90
28/3/2013	**265.00**	265.09	264.79	265.38	264.93	**265.00**	265.23	265.27	265.14
2/4/2013	**265.02**	265.08	264.78	265.24	264.88	**265.03**	265.28	265.38	265.03
3/4/2013	**266.00**	266.05	265.82	266.34	265.86	**265.94**	266.15	266.24	266.12
4/4/2013	**265.00**	265.58	265.10	266.03	265.53	**265.16**	265.67	265.71	265.53
5/4/2013	**265.00**	265.02	264.87	265.34	264.97	**264.95**	265.05	265.30	264.95
8/4/2013	**265.00**	264.96	264.85	265.26	264.81	**264.92**	265.08	265.30	264.96
9/4/2013	**265.00**	265.03	264.96	265.28	264.82	**264.94**	265.02	265.23	264.99
10/4/2013	**264.00**	263.85	263.85	264.13	263.65	**263.87**	263.84	264.12	263.74

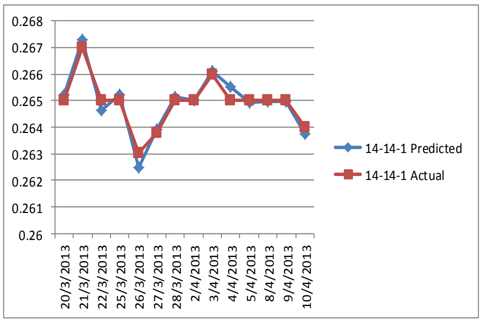

Fig 4.13 Graph of 14-16-1Predictive model.

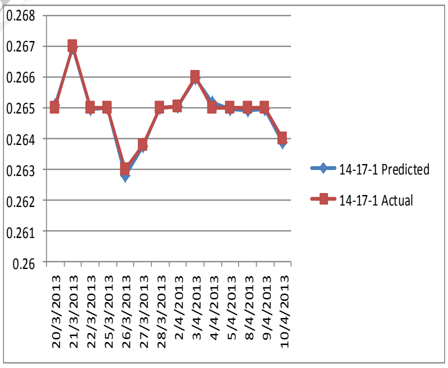

Fig 4.14 Graph of 14-17-1Predictive model.

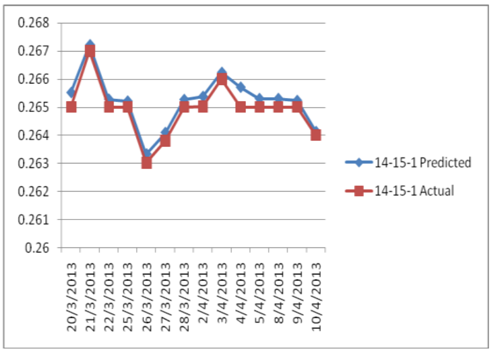

Fig 4.15 Graph of 14-15-1Predictive model.

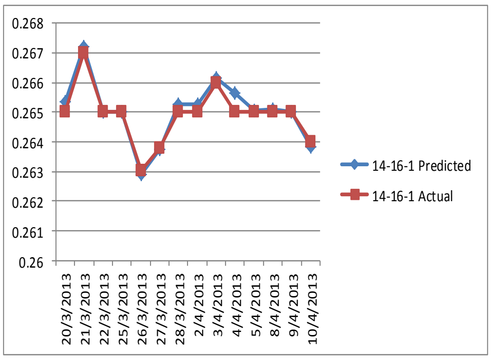

Fig 4.16 Graph of 14-16-1Predictive model

V. DISCUSSION OF RESULTS

The mean squared error was used to describe the performance of the neural network prediction. Table 4.1 shows the performance of Nestle Nigerian Plc. Prediction. The mean square error of the training, validation and testing are 4.6618e-6, 3.25520e-5 and 4.25777e-5 respectively. The values from the predictive model show a minimum amount of error. Table 4.2 shows the predicted values with different neural network predictive model. The table contains the sample data, the actual value, and values of different predictive models. The results from the different predictive models where compared with the actual value and it was observed that 14-19-1 predictive model gave the best prediction for Nestle Nigeria Plc.The result of 14-19-1 predictive model and the actual value are in bold for easy comparison and identification. Figure 4.5, 4.6, 4.7 and 4.8 shows the graphs of 14-21-1, 14-20-1, 14-19-1 and 14-18-1 predictive models respectively. The graphs demonstrate the closeness of the predicted value against the actual value, and it were seen from the graph that the prediction was done with minimum amount of error.

Table 4.4 shows the performance of Total Nigerian Plc. Prediction, the mean square error of the training; validation and testing are 3.07993e-6, 4.91378e-6 and 8.15871e-6 respectively. The values from the predictive model show a minimum amount of error. Table 4.5 shows the predicted values with different neural network predictive model. The table contains the sample data, the actual value, and values of different predictive model. The results from the different predictive models where compared with the actual value and it was observed that 14-20-1 predictive model gave the best prediction for Total Nigeria Plc.The result of 14-20-1 predictive model and the actual value are in bold for easy comparison and identification. Figure 4.9, 4.10, 4.11 and 4.12 shows the graphs of 14-21-1, 14-18-1, 14-19-1 and 14-20-1 predictive models respectively. The graphs demonstrate the closeness of the predicted value against the actual value, and it were seen from the graph that the prediction was done with minimum amount of error.

Table 4.3 shows the performance of Guinness Nigerian Plc. Prediction, the mean square error of the training; validation and testing are 8.29839e-7, 1.07882e-6 and 2.4488e-6 respectively. The values from the predictive model show a minimum amount of error. Table 4.2 shows the predicted values with different neural network predictive model. The table contains the sample data, the actual value, and values of different predictive model. The results from the different predictive models where compared with the actual value and it was observed that 14-17-1 predictive model gave the best prediction for Guinness Nigeria Plc. The result of 14-17-1 predictive model and the actual value are in bold for easy comparison and identification. Figure 4.13, 4.14, 4.15 and 4.16 shows the graphs of 14-16-1, 14-17-1, 14-15-1 and 14-16-1 predictive models respectively. The graphs demonstrate the closeness of the predicted value against the actual value, and it were seen from the graph that the prediction was done with minimum amount of error.

VI. CONCLUSION

The result shows that using hybridize factors input variables gives a better result in stock market prediction with minimum amount of error. It was also observed from the experimental results that optimal prediction can be achieved by varying the number of the hidden neuron. The initialization scheme may be improved by estimating weights between input nodes and hidden nodes, instead of random initialization. Enrichment of more relevant inputs such as fundamental data and technical data from derivative markets may improve the predictability of the network. Applying Neural Network back propagation learning algorithm in training data for stock prediction has been shown in this paper to be an efficient tool for stock prediction.

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