ISSN 1512-1232

UTILIZING ARTIFICIAL NEURAL NETWORK FOR PREDICTION IN THE NIGERIAN STOCK MARKET PRICE INDEX

[1]Bello, Muhammad Yahuza, [2]Chiroma, Haruna

[1]Bayero university kano, faculty of science, Mathematical science programme, P.m.b 3011 Kano, Nigeria
[2]Federal college of education (technical), school of science, computer science department p.m.b 60 Gombe, Gombe State, Nigeria freedonchi@yahoo.com

Abstract

This paper utilize ANNs model to predict closing price of AshakaCem Security in Nigeria Stock Market price index. In this paper, AshakaCem Security historical technical data were collected for four years trading period (2005 – 2008), the data was partition into training, cross validation and testing set in the ratio 70%:10%:20% respectively. Architectural configuration of Feed Forward Artificial Neural Networks (FFANN) with parameters of three (3) layers, four (4) input nodes, one (1) hidden layer, eighteen (18) hidden nodes, one (1) output layer and one (1) output node was obtained and FFANN was build with the calibrations, trained with 268 exemplars, cross validated with 37 exemplars and tested on 76 exemplars and evaluated on four (4) performance indicators which include Mean Square Error (MSE), Correlation Coefficient (r), Normalize Mean Square Error (NMSE) and Mean Absolute Error (MAE). The technical data were subjected to sensitivity analysis. FFANN predictor was developed and modeled historical trading data of AshakaCem Security and pattern was captured in the historical data with a trend accuracy of 80%, Efficient Market Hypothesis was contradicted in this paper and sensitivity analysis shows that previous closing price (pclose) is the most significant input on FFANN predictor output. FFANN predictor build was evaluated and result shows that MSE = 3.59739909, NMSE = 0.039391504, MAE = 1.3407 and r = 0.981331937. It is possible to trained ANNs with controlled parameters using technical data of AshakaCem Security to capture pattern in the historical data and generalize well on unseen data.

Keywords*: Nigeria Stock Market, Historical Data, AshakaCem Security, Artificial Neural Networks.*

1. INTRODUCTION

The main models use for prediction in stock market are Technical, Fundamental and Traditional time series analysis. Indexes use in technical analysis for prediction of share prices are mostly charts and moving averages, the chart depicted can be misinterpreted by investors which is misleading and moving averages generate poor signals. Fundamental analysis uses companies' financial report, price of related commodity, revenues, inflation rate and other vital information to predict a share price of a stock. Unfortunately, automation and interpretation of all those knowledge is difficult and it's hard to time the market. Figures can easily be concocted in a company financial report and use it to miss lead investors and financial experts. Traditional time series analysis uses regression for share price prediction but its accuracy decreases as period of prediction increases.

Prediction using Artificial Neural Networks (ANNs) model outperform Moving Average, Regression, Ordinary Least Square (Klassen, 2005; Kalyvas, 2001; Olson and Mossman, 2002; Robles and Naylor,1996; Shamchmurove and Witkowska 2000; Moody,1995; Lawrence, 1997;

ISSN 1512-1232

Stalinski and sorin,2006). Efficient Market Hypothesis (EMH) says, there is no room for making profits from stock market by predicting share price of a stock(Kalyvas 2001; Januskevicus 2003; Vanston 2005; Malkiel 1999 cited in Tsang et al 2007;), so far there is no consensus on acceptance or rejection of the hypothesis. Is very difficult to develop a single model and use it for prediction of security prices in different stock markets with various securities, studies have showed that each market and security require its own model for prediction (Dutta, Jha, Kumar, and Mohan, 2006). Base on information at disposal, there is no any extensive research work that has being reported alone these line in Nigerian context despite several empirical studies proved that prediction of share prices of a stock in a stock market using ANNs model is better than the current analytical techniques presently in use by financial expert in Nigeria.

This paper build a Feed Forward Artificial Neural Network Predictor (FFANNP) and was able to capture a pattern in the historical data of AshakaCement (AshakaCem) security of the Nigeria Stock Market (NSM) and predicted the closing prices of the security with a trend accuracy of 80%. EHM is contradicted in this paper.

2. RELATED WORK

2.1 FEED FORWARD ARTIFICIAL NEURAL NETWORKs

FFANN is a category of ANNs that collect historical data from input node and flow to a single direction towards output nodes where result is collected. Connection between output and input does not exist in this category. Perceptron is one of the earliest form of this type of Networks category that perform classification and evaluation of task in different areas. Feed forward back propagation Neural Networks introduced hidden layer which made it possible to solve non-linear problems. Feed Forward Neural Network is required to be trained with historical data which target value is known, using any suitable training algorithms, in so doing, the Network acquire new knowledge base on pattern learn from historical data and be able to generalized on data it has never seen called test set (Kanji, 2008). This is the category of ANNs deployed in this paper, there are other categories of ANNs which include self-organizing and Hopfield but their details is beyond the scope of this work.

> ``ANNs can be visualized as a mechanism for learning complex non-linear patterns in data. A key differentiator from other computer algorithms is that to a very limited extent. They model the human brain. This allow them to learn from experience that is by training rather than being programmed'' (Threapleton and Wilson, 2003) cited in (Ajakaiye, Adeyemo, Osofisan and Olowu, 2006:10).

3. MATERIALS AND METHODS

3.1 MATERIALS

A laptop computer system with a processor speed of 1.60 GHZ, RAM of 1 Gb, HDD 140 Gb and a 32 bit operating system type. Software used were, Windows Vista Business as operating system and Neuro Solutions 5.0 implemented with back-propagation training algorithms.

3.2 DATA ACQUISITION

Historical data were collected for a period of four years (2005-2008), the data was sourced from Sigma Securities Limited, a member of the Nigeria Stock Exchange. The data contains full information on technical data including previous closing price (pclos) previous closing price (pclose), closing price (close), open price (open), volume of shares traded (volume), highest price reached (high), lowest price reached (low) and trading date (date) were all provided. For the

ISSN 1512-1232

purpose of this paper, Ashaka Cement (AshakaCem) security was selected and all technical data related to the security was extracted from the share price index in securities index of Nigeria Stock Market.

3.3 DATA PRE-PROCESSING

Days without trading (weekend and public holidays) were neglected. Hcikel & kanus (1988) hold the position that, days with no trading can be neglected and use only trading days. Systematic sampling was used on the data using $k = \frac{N}{n}$

Where N = Trading Days for four years (2005-2008), n = Desired Samples of Trading Days, k = Sampling Interval,

N = 763, n = 383, $k = \frac{763}{383} = 1.997 \approx 2$

The data was not normalized because (Vanston, 2005) opposed normalization which argue that the use of raw data value is prefer so as to prevent destruction of original pattern in the time series.

3.4 EXPERIMENT

Inputs to FFNN models were technical data related to AshakaCem security which are pclose, open, low, high and Close price was the target variable. The collected data were partition in to training, validation and testing in a ratio 70%, 10% and 20% respectively. Architectural configuration of the FFNN model has three layers, four input nodes, one hidden LAYER ,eighteen hidden nodes , one input and output layer respectively. The model was trained with 268 exemplars, momentum of 0.5,1200 epochs and was run 4 times.

training was stop when cross validation stop improving and run for 100 epochs without improvement. In this paper over-training & under training were able to be avoided successfully.

3.5 SENSITIVITY ANALYSIS

The input variables were subjected to sensitively analysis.

3.6 CHOICE OF PERFORMANCE METRICS

In this paper, 20% of the data (76 exemplars) that the model have never seen was reserved and tested on FFANNP, performance was evaluated on all the following performance indicators: Mean Square Error (MSE), Correlation Coefficient (r) , Mean Square Error (NMSE) and Mean Absolute Error (MAE).

4. RESULT ANALYSIS AND DISCUSSION

4.1 RESULTS

Figure 4.1 is a plot of AshakaCem security close values over a period of time, the vertical axis indicate share prices of the security in Naira (N) and kobo (K) and horizontal axis indicate trading periods (2005 - 2008) starting from first trading day in January 2005 with a closing share price of N23:00 move upward to reached a peak share price of N84:89k and fall down to N13:99k in the last trading day in December, 2008.

ISSN 1512-1232

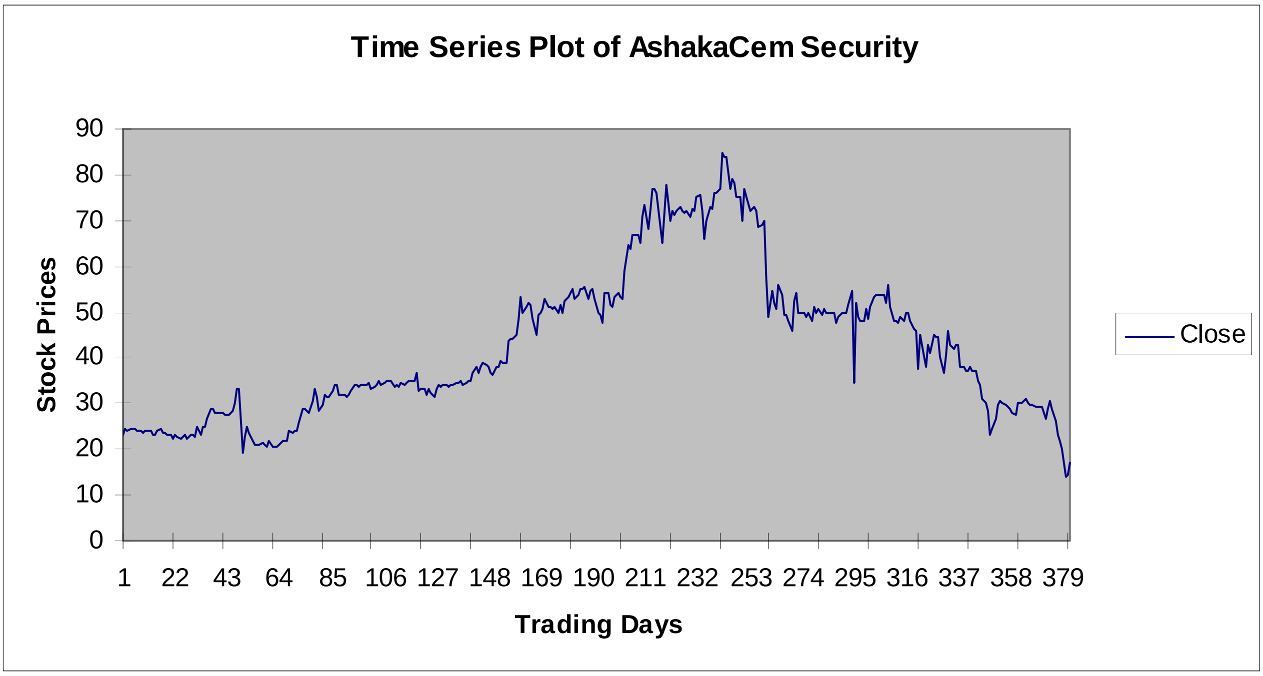

Figure 4.1: Closing price for the Period (2005 - 2008)

The network was run 4 times with different random initialization weights, average MSE is computed by averaging MSE over 4 runs at each epoch . The high (average + 1 standard deviation) and low (average – 1 standard deviation) standard deviation boundaries are shown on figure 4.2 using dashed line of the same colour as average line (the standard deviation is computed across 4 runs at each epoch). Average cross validation MSE and corresponding standard deviation boundaries are also shown on figure 4.2.

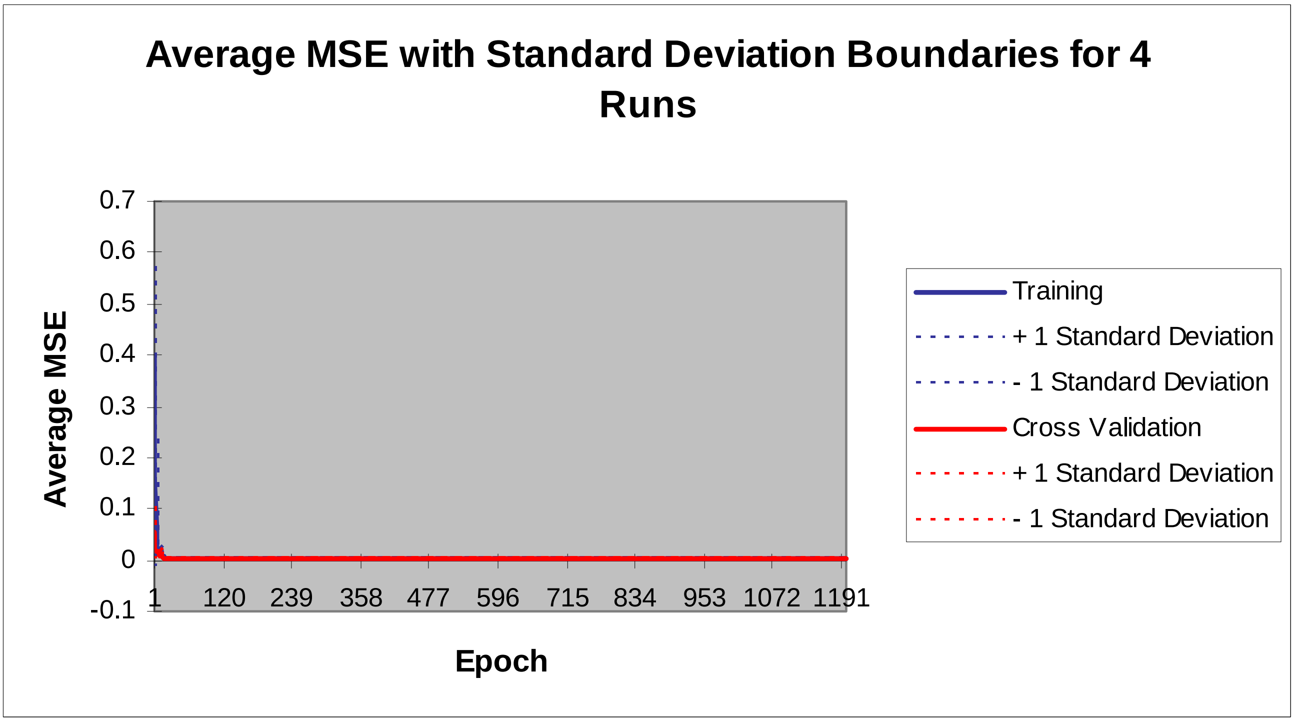

Figure 4.2: Average MSE Versus Epoch

ISSN 1512-1232

All Runs	*Training Minimum*	*Training Standard Deviation*	*Cross Validation Minimum*	*Cross Validation Standard Deviation*
Average of Minimum MSEs	0.001059444	4.84266E-05	0.000638898	6.6916E-05
Average of Final MSEs	0.001059444	4.84266E-05	0.000638898	6.6916E-05

Table 4.1: Minimum Training and Cross Validation MSE over 4 Runs

From table 4.1 the average of minimum training MSE is 0.001059444 over 4 runs and final training MSE is 0.001059444 along with corresponding standard deviation of 4.84266E-5 for both average minimum MSE and average final MSE, average of cross validation MSE is 0.000638898 and average of final cross validation MSE is 0.000638898 over 4 runs and corresponding standard deviation of 6.6916E-5 for both average MSE and average final MSE respectively. This shows improvement of cross validation over training.

Best Networks	*Training*	*Cross Validation*
Run #	1	2
Epoch #	1200	1200
Minimum MSE	0.000990442	0.00058809
Final MSE	0.000990442	0.00058809

Table 4.2: Best Network out of 4 Runs

Table 4.2 shown the best training MSE is 0.000990442 out of 4 runs at 1200 epochs and this occurred at run 1 and final MSE is 0.000990442. The best cross validation MSE out of 4 runs is 0.00058809 at 1200 epochs and occurred at run 2 and the final cross validation MSE for this best run is 0.00058809. This shown the best network occurred at run 2. Figure 4.3 report a plot of all four runs (run#1, run#2, run#3 and run#4) use to run the neural network model each run begins with different random initial weights. Figure 4.3 shows how error is drastically decreasing on training and rapid convergence is on run#1.

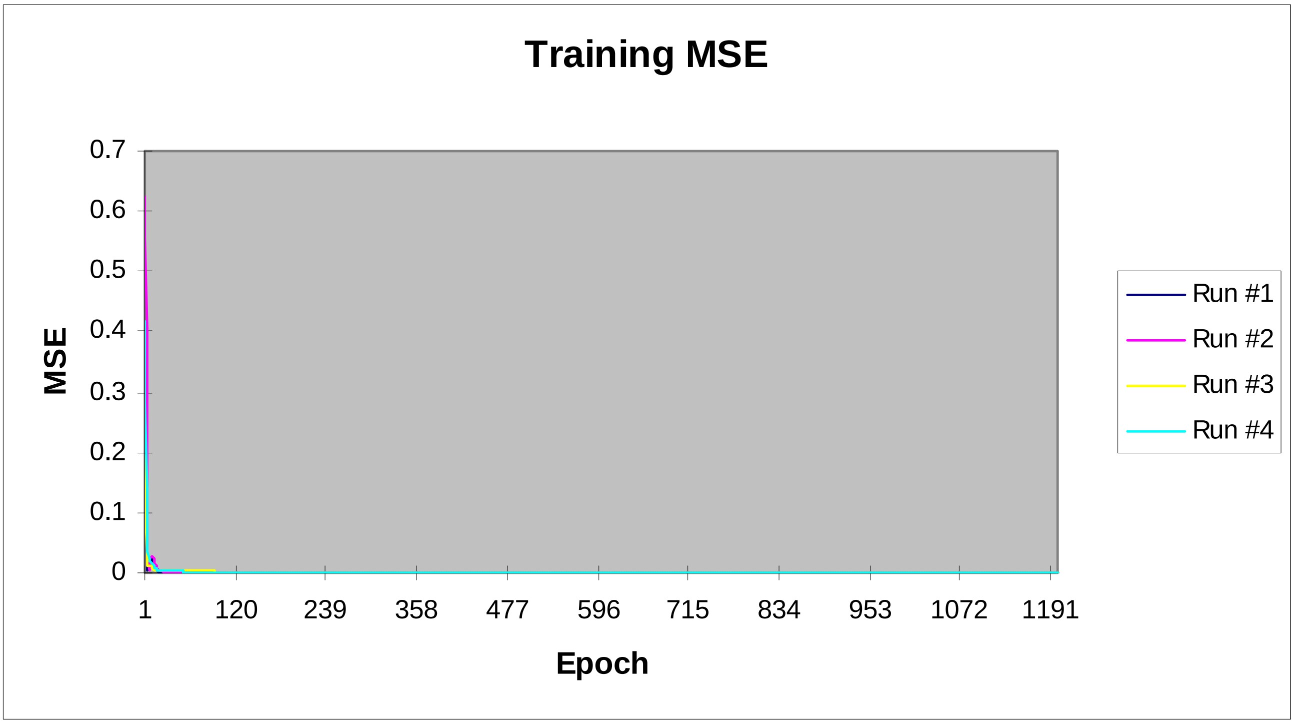

Figure 4.3: MSE Versus Epoch

ISSN 1512-1232

Figure 4.4 is a plot of cross validation MSE and Epoch for each of the four runs (run#1, run#2, run#3 and run#4) .

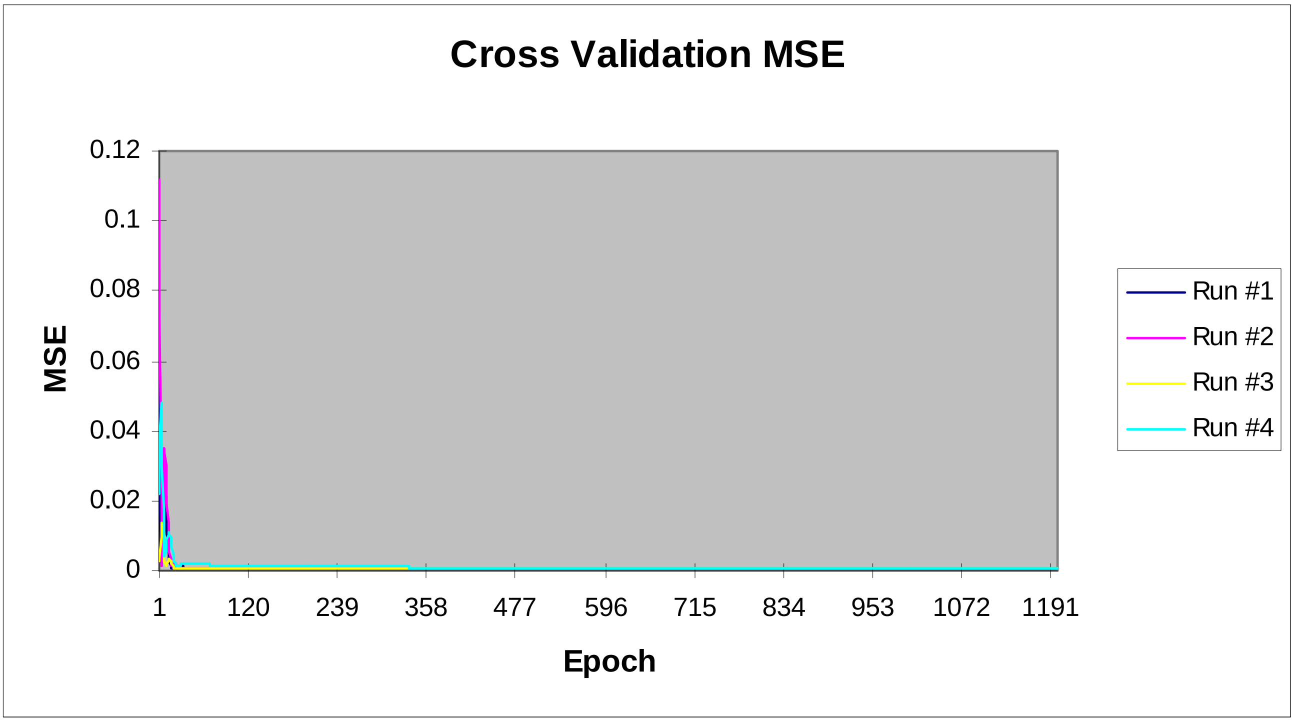

Table 4.4: Cross Validation MSE Versus Epoch

Figure 4.5 is a 3 dimensional plot of table 4.3 indicate significant influence of technical input on FFANNP output, it shows that Pclose has the highest significant influence followed by High, Open and Low respectively.

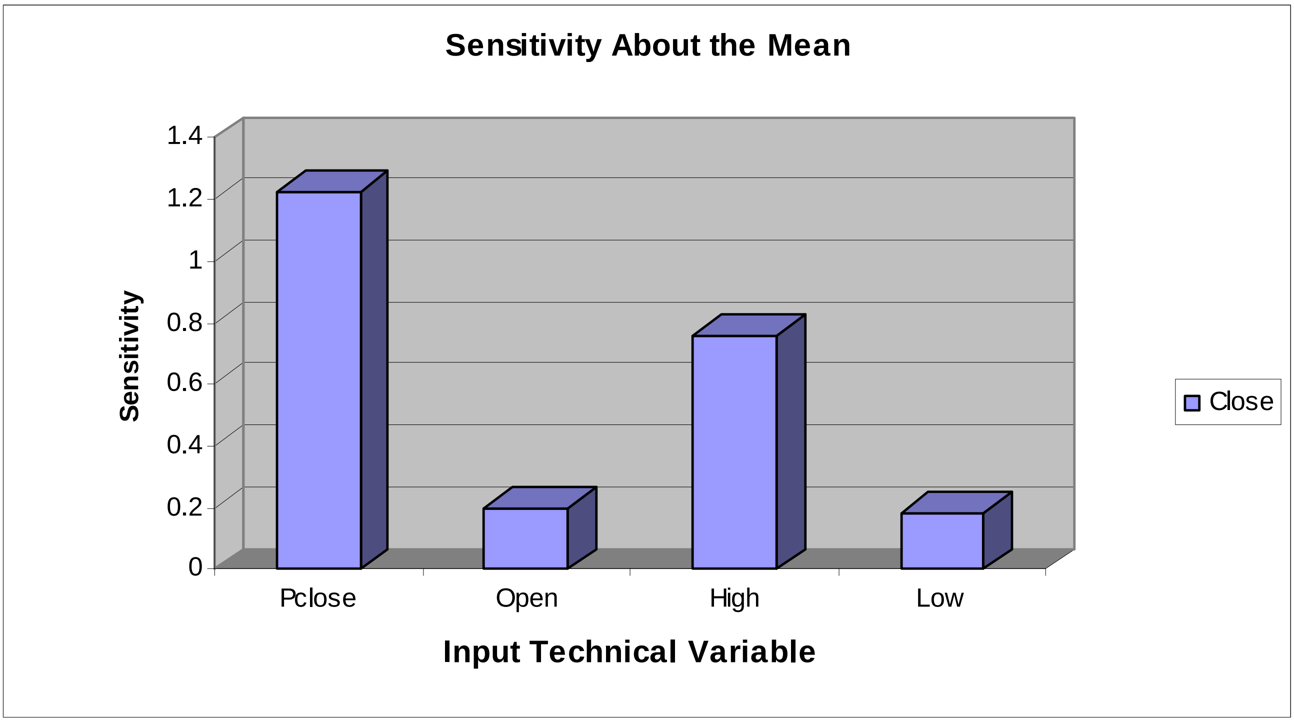

Figure 4.5: Result of Technical Input Sensitivity Analysis

ISSN 1512-1232

Sensitivity	*Close*
Pclose	1.224736491
Open	0.198549386
High	0.758088232
Low	0.179797526

Table 4.3: Standard Deviation for each Technical Input

Figure 4.6 is the FFANN predictor constructed using Neural Builder on Bread Board .

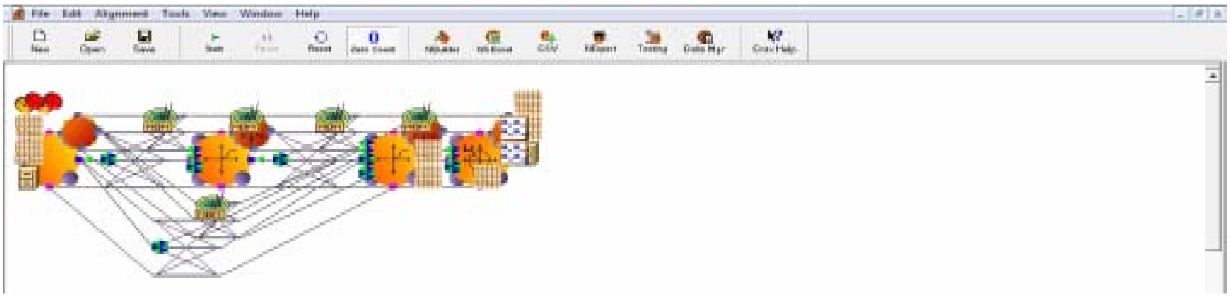

Figure 4.6: FFANNP

Figure 4.7 is the result reported when FFANNP was tested on data it has never seen, showing plot of close values predicted by FFANNP as dashed colour line and actual close values was plotted as the solid colour line of the same colour.

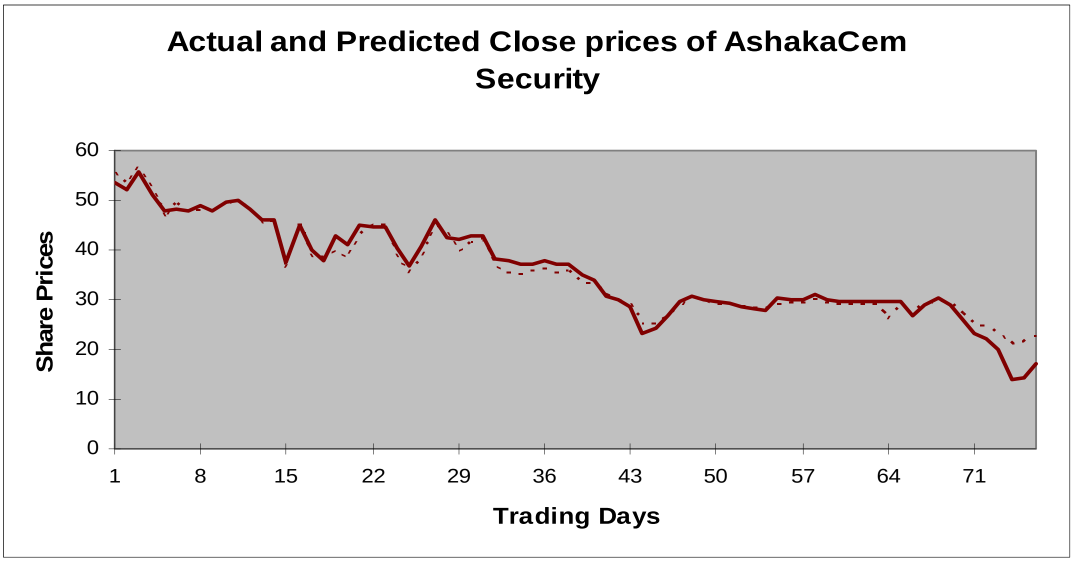

Figure 4.7: FFANNP Test Result

Performance	*Close*
MSE	3.597939909
NMSE	0.039391504
MAE	1.340726836
Min Abs Error	0.02866186
Max Abs Error	7.156101536
r	0.981331937
TA	80%

Table 4.4: FFANNP Performance Indicators

ISSN 1512-1232

Table 4.4 is the result of performance evaluation for the FFANNP which indicate that MSE = 3.60 indicate the error between predicted close by FFANNP and actual close, NMSE = 0.04 means that the prediction is doing good than the series mean, MAE = 1.34 with Minimum Absolute Error of 0.03 and Maximum Absolute Error of 7.16 shows that the prediction is good, r = 0.98 indicate that the fit of FFANNP to the data is very good.
Trend Accuracy (TA) of 80% was achieved.

4.2 EFFICIENT MARKET HYPOTHESIS

According to Fama (1970) EMH specifically is divided into three forms as follows:

4.2.1 **Weak Form of EMH**: State that technical data of a security cannot be use to predict its future share prices.

4.2.2 **Semi – Strong Form of EMH**: State that once information is made public it cannot be use to predict future share price of a security.

4.2.3 **Strong Form of EMH**: State that investors cannot predict share price of a security no matter how information is at their disposal.

4.3 TESTING THE EMH

The share price of AshakaCem Security was able to be predicted with a TA of 80% using technical data of the security as basis and this contradict weak, Semi – Strong and strong form of EMH and conclude that EMH is inefficient.

4.4 DISCUSSION OF RESULTS

It was observed that the Neural Network model was over trained which resulted to over- fitted error and it perform poorly on out of sample data (Klassen, 2005). If training process is not carefully controlled, the neural network model can over fit the data and give a poor generalization (Lawrence 1997; Vanston 2005) this paper contradict the statement of (Klassen, 2005) and support that of (Lawrence 1997; Vanston 2005) because in this paper over-fitted error was controlled successfully using cross validation, therefore (Klassen, 2005) statement is a weak statement.
Sensitivity analysis of technical input variables of AshakaCem Security shows that Pclose is the most highly influencial variable to the output followed by High, open and Low respectively, this affirmed the sensitivity analysis of inputs variables carried out in the work of (Doeksen, Abraham, Thomas and paprzycki, 2005) in their work sixteen (16) technical inputs were subjected to sensitivity analysis and it was found that the four most significant technical variables in decreasing order were Previous close price, High, Open and Low respectively.
The 80% prediction accuracy achieved by FFANNP in this paper was closer to prediction accuracy published in other works such as (Pan, Tilakaratne and Yearwood, 2005) who achieved 80.26% prediction accuracy, (phua, Ming and Lin, 2000) with 81% prediction accuracy and (Abdo and Panalian, n.d.) 85%. There are large number of authors who documented the use of ANNs model for prediction in various stock markets across the globe, this paper has clearly added to it. The result obtained after EMH was test and documented in this paper contradict EMH. There are large amount of documented work that find no evidence against EMH such as, but not limited to (White 1988; Tsang et al 2007;) while the work of (Tsibouris and Zeidenberg 1995; Lawrence 1997; Quah and Srinivasan 1999; Man-Chung, chi-Cheong and Chi-Chung n.d.; Januskevicius 2005; Vanston 2005;) among so many others contradicted EMH. This paper has added to it

5. CONCLUSION

The findings emanated from this paper resulted to the following conclusions:

It is possible to trained ANNs with highly controlled three layers of nodes (4 – 18 – 1) structure using technical historical data of AshakaCem security to capture pattern in the historical data and generalized well on unseen data.
The efficacy of EMH is questionable base on experimental result of this paper, therefore contradicted.
Pclose is the most significance input variable.
The considered view of this paper is that, there is bases for financial expert in Nigeria currently using analytical techniques for share price prediction to adopt ANNs model as additional or complementary tool for share price prediction in NSM price index.

REFERENCES

1. Abdoh, H.T. and Panahian, H. (n.d.). *Stock price prediction by artificial neural network: A case study of Tehran's stock exchange*. Retrieved, May 6, 2008, from http://www.abdoh.net/abase/upload/TSE-pp.pdf.
2. [2] Doeksen, B., Abraham, A., Thomas, J. and Paprzycki, M. (2005). Real stock trading using soft computing models. *Proceedings of international conference of Institute of Electrical and Electronics Engineering* 2:162-167.
3. [3] Dutta, G., Jha, P., Kumar, A.L. and Mohan, N. (2006). Artificial neural network models for forecasting stock price index in the Bombay stock exchange. *Journal of Emerging Market Finance* 5(3):283-295.
4. Fama, E. (1970). Efficient capital markets: a review of theory and empirical work. *Journal of Finance 25:383 – 417.*
5. Januskevicius, M.(2003). *Testing stock market efficiency using neural networks: case of Lithuania*. An unpublished PHD thesis, Stockholm school of economics Riga.
6. Kanji, G.D.(2008). *Vision system for mobile robot based on line detection using the Hough transform and artificial neural networks*. An unpublished PHD thesis, school of engineering Robert Gordon University Aberdeen.
7. Kalyvas, E. (2001). *Using artificial neural network and genetic algorithms to predict stock market returns.* An unpublished MSC thesis, faculty of science and engineering University of Manchester.
8. Klassen, M. (2005). Investigation of some technical indexes in stock forecasting using neural networks. *Proceedings of World Academic of Science, Engineering and Technology* 5:75-79.
9. Kutsurelis, J. (1998). *Forecasting financial market using neural networks: an analysis of methods and accuracy*. Unpublished MSC thesis, naval postgraduate school, U.S naval academy California.
10. Lawrence, R. (1997). *Using neural networks to forecast stock market prices.* Retrieved May 3, 2008, from http://people.ok.ubc.ca/rlawrence/research/papers/nn.pdf.
11. Lucey, T. (2002). Quantitative techniques. Great Britain: MPG books ltd.
12. Man-Chung, C., Chi-Cheong, W. and Chi-Chung, L. (n.d.). Financial time series forecasting by neural network using conjugate gradient learning algorithms and multiple linear regression weight initialization. Retrieved June 23, 2008, from http://www.jurikres.com/down/financial%20forecasting%20and%20gradient%20descent%20.pdf.
13. Moody, J. (1995). *Economic forecasting: challenges and neural network solutions.* Retrieved May 3, 2008, from http://Neural.cse.ogi.edu/pub/neural/papers/moody95.macroeconomic.ps.z.
14. Pan, H., Tilakaratne, C. and Yearwood, J. (2005). Predicting Australian stock market index using neural networks exploiting dynamical swings and intermarket influences. *Journal of Research and Practice in Information Technology* 37(1):43-55.
15. Phua, P.K.H., Ming, D. Lin, W. Neural networl with genetic algorithms for stocks prediction. *Conference of the association of Asian-pacific Operation Research Society* 5-7 July, 2000.

ISSN 1512-1232

16. Quah, T.S. and Srinivasan, B. (1999). Improving returns on stock investment through neural network selection. *Journal of Expert System with Applications* 17:295-301
17. Robles, J.V. Applying neural networks in copper trading: a technical analysis simulation. *Third international conference on neural Networks in Capital Market*, 11-13 October 1995.
18. Shachmurove, Y. and Witkowska, D. (2000). *Utilizing artificial neural network model to predict stock markets*. Retrieved July 25, 2008, from http://www.econ.openn.edu/Centers/CARESS/CARESSpdf/00-11.pdf.
19. Stalinski, P. and Sorin, A.T. (2006). The determinants of foreign listing decision: neural networks versus traditional approaches. *International Research Journal of Finance and Economics* 4:220-231.
20. Tsang, P.M., Kwok, P., Choy, S.O., Reggie, K., Ng, S.C., Mark, J., Jonathan, T., Koon, K. and Wong, T. (2007). Design and implementation of NN5 for Hong Kong stock market price forecasting. *Journal of Engineering Application of Artificial Intelligence,* 20:453-461.
21. Tsibouris, G. and Zeidenberg, M. (1995). Testing the efficient market hypothesis with gradient descent algorithms: neural network in the capital markets. Pradon: John Wiley and sons.
22. Olson, D. and Mossman, C. (2002). Neural network forecasts of Canadian stock returns using accounting ratios. *International Journal of Forecasting* 19: 453-465.
23. Vanston, B.J. (2005). *Trading in the Auatralian stock market using artificial neural networks*. An unpublished PHD thesis, school of information technology Bond University.

Article received: 2010-08-08