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PREDICTING THE NIGERIAN STOCK MARKET USING ARTIFICIAL NEURAL NETWORK

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Abstract: *Forecasting a financial time series, such as stock market trends, would be a very important step when developing investment portfolios. This step is very challenging due to complexity and presence of a multitude of factors that may affect the value of certain securities. In this research paper, we have proved by contradiction that the Nigerian stock market is not efficient but chaotic. Two years representative stock prices of some banks stocks were analyzed using a feed forward neural network with back-propagation in Matlab 7.0. The simulation results and price forecasts show that it is possible to consistently earn good returns on investment on the Nigerian stock market using private information from an artificial neural network indicator.*

Keywords: neural networks, stock market, efficiency theory, chaotic theory, forecasting.

INTRODUCTION

Despite significant advances in certain areas of mathematical finance, there is still no formal model that describes the mechanics of the stock market (Vanstone, 2005). What has rather evolved are two distinct investment paradigms based on the efficiency theory, and chaotic theory. Since the early work of Fama, it is common to discuss three forms efficiency when examining the Efficient Market Hypothesis (EMH). EMH states: “that a market is ‘weak form efficient’ if it is not possible to consistently earn excess returns using past prices and returns. A market is ‘semi-strong efficient’ if it is not possible to consistently earn excess returns using public information. A market is ‘strongly efficient’ if it is not possible to consistently earn excess returns using any information, including private information” (Fama, 1969).

Acceptance of the efficiency of the stock market results into a passive investment strategy while a refusal of the EMH leads to an aggressive and active investment drive. An active investment strategy logically emanates from the argument that there exists a random and deterministic pattern in the stock market time series (Fatma and Bouri, 2009). Chaos theory analyses a process under the assumption that the process is partly deterministic, and partly random. Chaos is a non-linear process which appears to be random. Various theoretical tests have been developed to prove that a system which is chaotic has chaos in its time series. Chaos theory is an attempt to show that order does exist in apparent randomness.

From a trading perspective, market efficiency generally implies that it is impossible to repeatedly earn reasonable returns on investment using any available information. But security prices change due to arrival of new information (Vanstone, 2005). Implicitly, the arrival and timing of new information is unpredictable; hence in an efficient market, security prices should appear to be generated randomly.

Chaos theory is a relatively new approach to modeling nonlinear dynamic systems like the stock market. A chaotic system is a combination of a deterministic and random process. By implying that the stock market is chaotic and not simply random, chaos theory contradicts the market efficiency theory.

Artificial neural networks have the ability to capture both the deterministic, non-linear random patterns in the stock market time series data due largely to its learning capacity (Arnold, 2003). It is our goal therefore in this research paper to exploit the learning capability of a feed forward neural network with back-propagation for the prediction of daily stock prices of securities quoted on the Nigerian Stock Exchange. Stock market forecasting is the process of making projections about future price performance based on existing historical data (Siram, 2005). With these historical stock prices, we shall attempt to make projections to further show that the Nigerian stock market is not efficient but chaotic.

The research paper is organised as follows. The second section is survey of related literatures on stock market analysis. The neural network model and methodology is presented in section three. While the market projections and simulation results are presented in section four with a conclusion.

LITERATURE REVIEW

Technical analysis of a weak form efficient market based on the overraction theory is deemed void; as proved in the works of Zhang and Kyrzanowksi in the study of the Canadian stock market. The overreaction theory assumes that knowing the past stock performance enables investors to forecast future yields. Analyzing the TSX stocks over a 38 years period they showed that the Canadian stock market is weak form efficient (Fatma and Bouri, 2009).

To support the semi-strong efficiency, Fama in his study concluded that market players appear to anticipate new information in advance which stabilizes the prices of the stocks even when the news is released (Fama, 1969). The strong-form efficiency means that the professional industry insiders are not able to beat the market. This was evidenced in a research study conducted by Jenson on about one hundred and fifteen mutual funds between 1955 and 1964. Excluding management fees and other transaction charges, a negative return of -2.5% was posted (Fama, 1969).

A neural network is a computer program that recognizes patterns and is designed to take pattern of data and generalize from it (Ravichandran et al, 2005). An essential feature of this technology is that it improves it performance on a particular task by gradually learning a mapping between inputs and outputs. There are no set of rules or sequences of steps to follow in generalizing patterns of data. The network is designed to learn a non-linear mapping between the inputs and output data, Generalization is used to predict the possible outcome for a particular task. This process involves two phases known as the learning phase (training) and the testing phase (forecasting).

Regression models have been traditionally used to model the changes in the stock markets. However, these models can predict linear patterns only. The stock market returns change in a non-linear pattern such that neural networks are more appropriate to model these changes (Ravichandran et al, 2005). Back propagation neural networks are independent of the sequence in which the inputs are presented.

Research studies have shown that back propagation networks may be used for prediction in financial market analysis. Refenes et al (1993) compared back propagation networks and regression models both using the same stock data. In comparison with regression models, back propagation proved to be a better predictor. The results showed that the mean squared Error (MSE) for the NN was lower than the multiple Linear Regression (MLR) models.

Kryzanowskwi et al (1993) using Boltzmann machine trained an ANN with 149 test cases of positive (rise in the stock price) and negative (fall in the stock price) returns for the years 1987 – 1989 and compared this to training the network with positive neutral (unchanged stock price) and negative returns for the same 149 test cases for the years 1987 – 1989. This network predicted 72% correct results with positive and negative returns. However, the network predicted only 46% correct results with positive, neutral and negative returns.

Artificial neural networks (ANN) are defined as an information-processing paradigms inspired by the methods by which the mammalian brain processes information (Caianiello, 1999, and Lippman, 1987). There are assortments of mathematical models that imitate some of the observed phenomena in a biological nervous system, most importantly, adaptive biological learning. One unique and important property of an ANN model is the exceptional structure of the information processing system (Shapura, 1996). It is made of a number of highly interconnected processing elements that are very similar to neurons and are joined by weighted connections that are very similar to synapses.

ANNs have been used by several researchers for developing applications to help make more informed financial decisions. Simple neural network models do a reasonably good job of predicting stock market price motion, with buy/sell prediction accuracies considerably higher than traditional models (Thawornwong et al., 2001). This performance is being improved by adding more complexity to the network architecture and using more historical data. Different types of network architectures such as multilayer perceptrons (MLP), generalized feed forward (GFF) networks and radial basis functions are becoming increasingly popular and are being tested for higher accuracy.

Many researchers are also investigating the possibility of adding additional indicators that may help the neural network improve training and performance while testing on production data. Neural network modeling shows potential for minimizing forecasting errors due to the improvements made in training algorithms and increased availability of indicators.

METHODOLOGY

The Neural Network Model

Artificial Neural Network (ANN) is an information processing system that has been developed as generalizations of mathematical models of human neural biology (Figure 1).

ANN is composed of nodes or units connected by directed links. Each link has a numeric weight (W is the weight matrix).

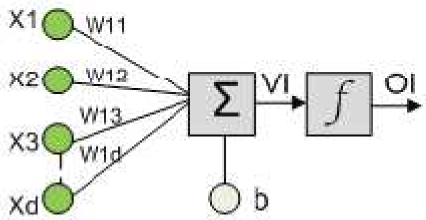

Fig 1: Mathematical model of the artificial neuron
(Source: Matlab Documentation, 2004)

Notice that in Figure 1 we have included a bias *b* with the purpose of setting the actual threshold of the activation function.

$$v_i = \sum_{j=1}^{d} w_{ij} x_j \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

$$o_i = \Upsilon(v_i) = \Upsilon\left(\sum_{j=1}^{d} w_{ij} x_j\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$$

$$w = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{1d} \\ w_{21} & w_{22} & w_{23} & w_{2d} \\ w_{31} & w_{32} & w_{33} & w_{3d} \\ w_{m1} & w_{m2} & w_{m3} & w_{md} \end{bmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3$$

where Υ is the activation function, x_j is the input neuron *j*, o_i is the output of the hidden neuron *i*, and W is the weight matrix. The NN learns by adjusting the weight matrix (Matlab Documentation, 2004).

Therefore the general process responsible for training the network is mainly composed of three steps:

1. Feed forward the input signals
2. Back propagate the error
3. Adjust the weights

Basic structure of a NN is depicted in Figure 2, the input data being fed up at the input layer and the output data being collected at the output layer.

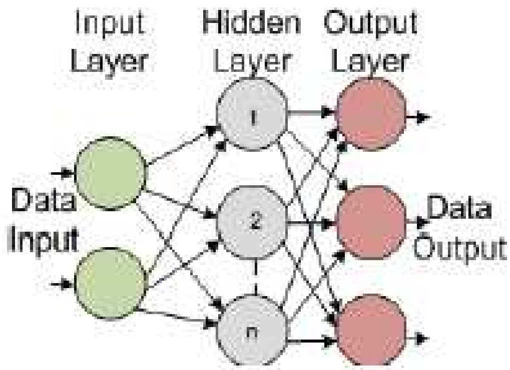

Fig 2: Basic structure of a NN

Basic Working: A neuron is basically a cell which accumulates electrical signals with different strengths. What it does more is that it compares the accumulated signal with one predefined value unique to every neuron. This value is called bias. This is the illustrated in figure 3.

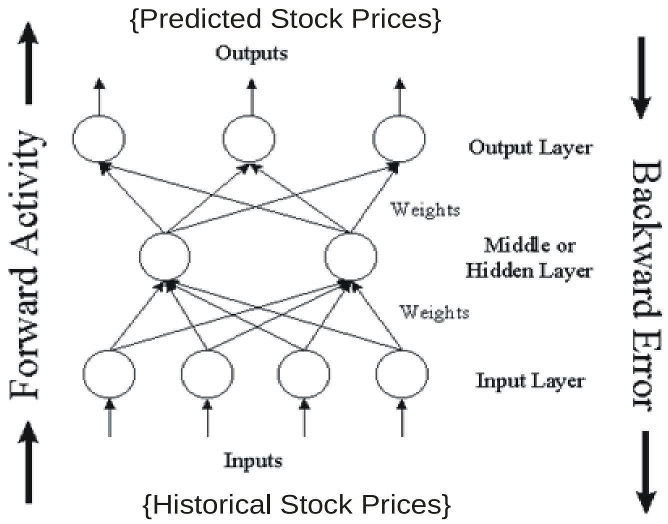

Fig. 3: Feed-forward NN with Backpropagation (FFNNB)
(Source: Caudill and Butler, 1992)

The circles in the image represent neurons. This network or more appropriately this network topology is called feed-forward multi layered neural network. It is the most basic and most widely used network. The network is multi layered because it consists of more than two layers. The neurons are arranged in a number of layers, generally three. They are input, hidden/middle and output layers. The names signify the function of the layer. This network is feed-forward, means the values are propagated in one direction only. There are many other topologies in which values can be looped or move in both forward and backward direction. But, this network allows the movement of values only from input layer to output layer.

Training the Neural Network

Once the network weights and biases have been initialized, the network is ready for training. During the training, the network is adjusted based on a comparison of the output and the target, as illustrated in figure 4.

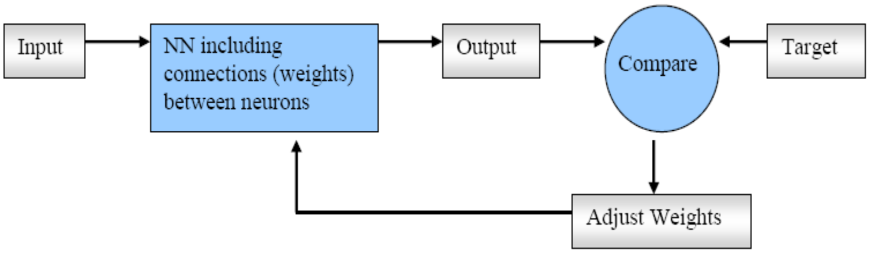

Fig. 4: Adjusting network based on a comparison of the output and the target (Source: Ball and Tissot, 2006)

The training process requires a set of examples of proper network behavior - network inputs (close prices) and target outputs. During training the weights and biases of the network are iteratively adjusted to minimize the network performance function. The most common performance function for feedforward networks is Mean Square Error MSE - the average squared error between the network outputs a and the target outputs.

Neural Network Development

Using Matlab, we created and trained (supervised learning) Feed forward Neural Networks (with backpropagation) for each of the selected banks (with model in Figure 5).

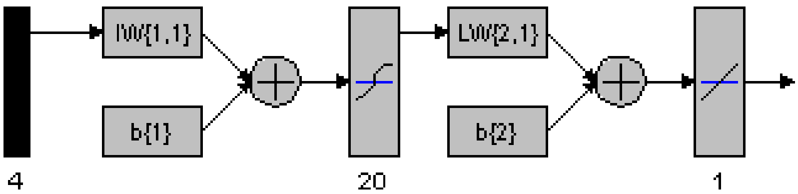

Fig. 5: Model of Network created by Matlab scripts.

The first step is to normalize the data. To do this we want to change each number into the percent movement from the previous day. We therefore preprocessed the stock prices in Microsoft Excel worksheet (using the formula = ((A – B)/B)*100. The network takes four-day price movements, and predicts the trend of the market. A 30 day (between 09-01-2010 and 10-19-2010) training data set was used for training the network. The forecast output is stored in the Forecast table for each trading day for all stocks respectively. The forecast table contains the results of the predictions. The Matlab scripts simulates the neural network; given price movements, say m1, m2, m3 and m4 it predicts the next day's market trend. Specifically, we use a four day price movement to predict the next market day's price direction.

CONCLUSION AND DISCUSSION OF RESULTS

Potential investors and active day stock traders need a proactive strategy to secure their investment portfolios. The Nigerian stock market is chaotic; hence it is predictable using neural networks. The use of artificial neural networks (ANNs) in a chaotic market does not require an understanding the market dynamics. This is why it is practically feasible and profitable to use machine learning systems like neural networks to predict the behaviour of financial instruments such as stocks. From our simulation and projection results (in the appendix) we can infer that:

- Reasonable profit can be obtained in stock markets (especially Nigerian stock market) trading with ANNs (appendix).
- When forecast to buy is realized, you have to later sell the stocks at a favorable price margin above your purchase price.
- Forecasts to sell therefore at the reasonably higher price may not be the next day. Hence, you have to hold your stock until the network provides favorable forecasts to sell.
- Against the next day, we predicted the market trend, with the ANN succeeding at the following rate:
  Access Bank Plc: 50%
  First Bank Plc: 83.33%
  UBA Plc: 83.33%

Hence on the Nigerian stock market, ANNs, appropriately deployed, is a 'money machine'. Thus in it contribution to knowledge this research paper exploit the learning capability of a feed forward neural network with back-propagation algorithm for the prediction of daily stock prices of the Nigerian Stock Exchange and consequently introduces another interesting way of wealth creation. ANNs can be appropriately deployed as a 'trading robot'.

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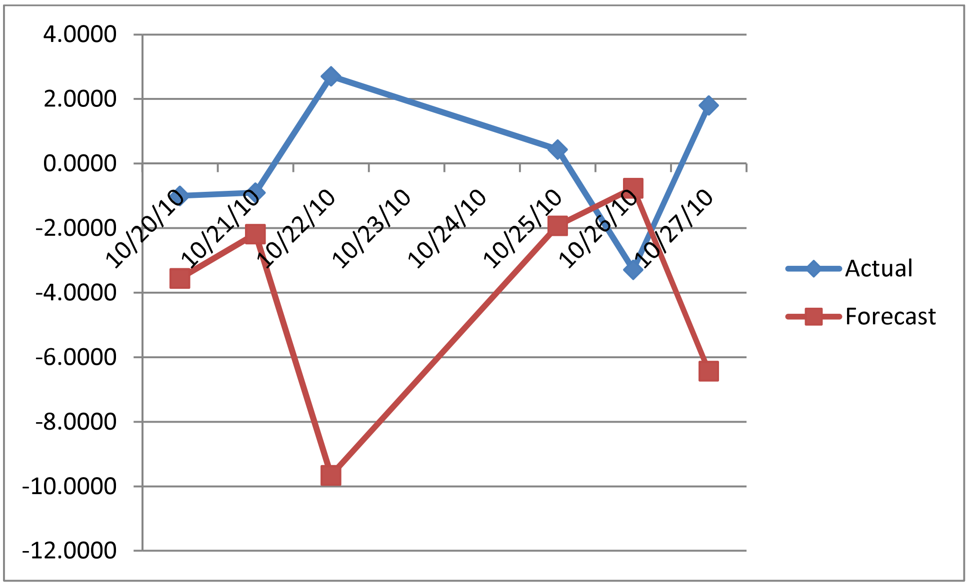
Tissot, and Ball(2006)

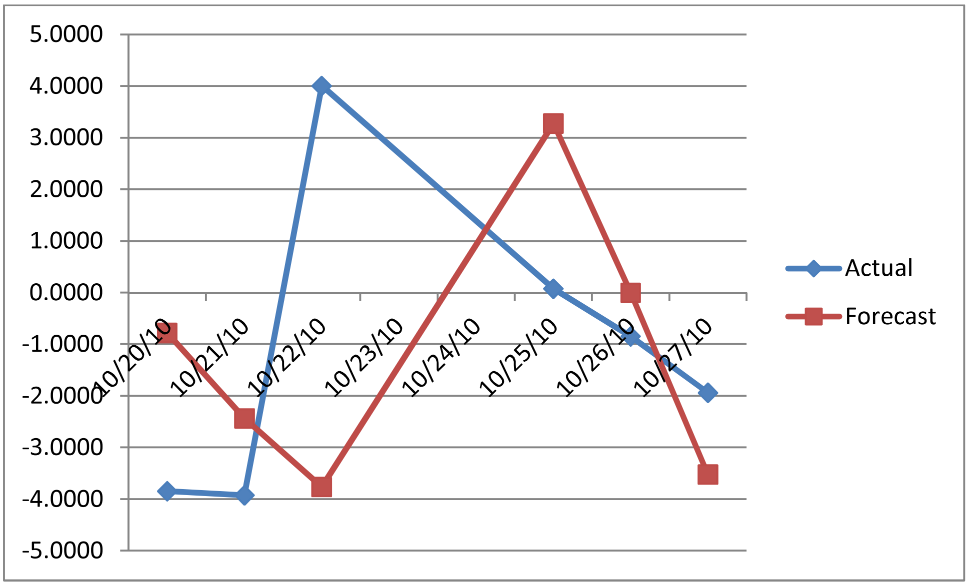
Appendix

Access Bank Forecasts							
	Day	Date	%PriceMove	Date	%PriceMove	Date	%PriceMove
	1	10/14/10	0.1076	10/15/10	-0.5376	10/18/10	0.3243
	2	10/15/10	-0.5376	10/18/10	0.3243	10/19/10	-2.694
	3	10/18/10	0.3243	10/19/10	-2.694	10/20/10	-0.9967
	4	10/19/10	-2.694	10/20/10	-0.9967	10/21/10	-0.8949
TargetDate	5	10/20/10	-0.9967	10/21/10	-0.8949	10/22/10	2.7088
		Forecast%	-3.5531	Forecast%	-2.1791	Forecast%	-9.6563
	Day	Date	%PriceMove	Date	%PriceMove	Date	%PriceMove
	1	10/19/10	-2.694	10/20/10	-0.9967	10/21/10	-0.8949
	2	10/20/10	-0.9967	10/21/10	-0.8949	10/22/10	2.7088
	3	10/21/10	-0.8949	10/22/10	2.7088	10/25/10	0.4396
	4	10/22/10	2.7088	10/25/10	0.4396	10/26/10	-3.2823
TargetDate	5	10/25/10	0.43956	10/26/10	-3.2823	10/27/10	1.80995
		Forecast%	-1.9232	Forecast%	-0.7561	Forecast%	-6.4252



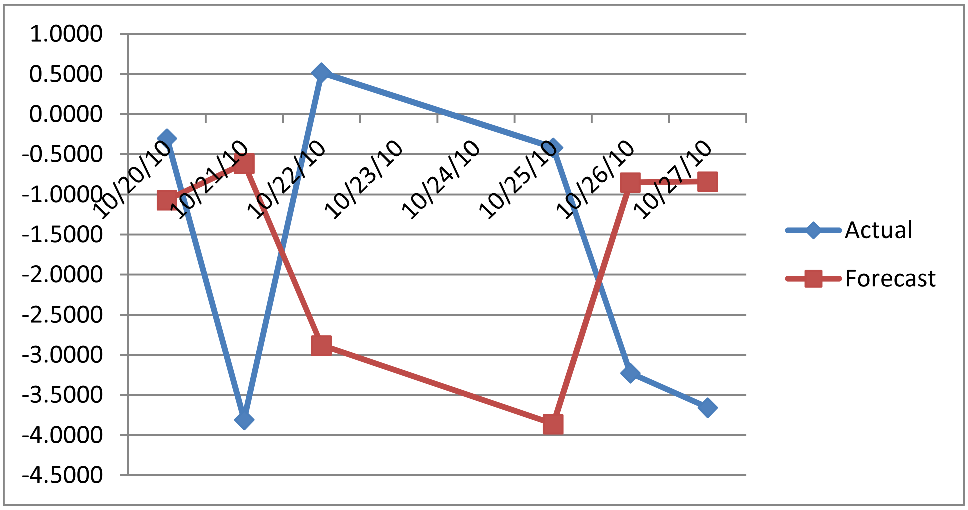
Access Bank Actual/Forecast's Chart

		First Bank Forecasts					
	Day	Date	%PriceMove	Date	%PriceMove	Date	%PriceMove
	1	10/14/10	0.0833	10/15/10	4.9917	10/18/10	4.9921
	2	10/15/10	4.9917	10/18/10	4.9921	10/19/10	2.0377
	3	10/18/10	4.9921	10/19/10	2.0377	10/20/10	-3.8462
	4	10/19/10	2.0377	10/20/10	-3.8462	10/21/10	-3.9231
TargetDate	5	10/20/10	-3.84615	10/21/10	-3.92308	10/22/10	4.003203
		Forecast%	-0.7783	Forecast%	-2.4351	Forecast%	-3.762
	Day	Date	%PriceMove	Date	%PriceMove	Date	%PriceMove
	1	10/19/10	2.0377	10/20/10	-3.8462	10/21/10	-3.9231
	2	10/20/10	-3.8462	10/21/10	-3.9231	10/22/10	4.0032
	3	10/21/10	-3.9231	10/22/10	4.0032	10/25/10	0.077
	4	10/22/10	4.0032	10/25/10	0.077	10/26/10	-0.8462
TargetDate	5	10/25/10	0.076982	10/26/10	-0.84615	10/27/10	-1.93949
		Forecast%	3.277	Forecast%	-0.0024	Forecast%	-3.5207



First Bank Actual/Forecast's Chart

UBA Forecasts							
	Day	Date	%PriceMove	Date	%PriceMove	Date	%PriceMove
	1	10/14/10	-2.3736	10/15/10	1.5856	10/18/10	3.9542
	2	10/15/10	1.5856	10/18/10	3.9542	10/19/10	0.2002
	3	10/18/10	3.9542	10/19/10	0.2002	10/20/10	-0.2997
	4	10/19/10	0.2002	10/20/10	-0.2997	10/21/10	-3.8076
TargetDate	5	10/20/10	-0.2997	10/21/10	-3.80762	10/22/10	0.520833
		Forecast%	-1.07	Forecast%	-0.6127	Forecast%	-2.8819
	Day	Date	%PriceMove	Date	%PriceMove	Date	%PriceMove
	1	10/19/10	0.2002	10/20/10	-0.2997	10/21/10	-3.8076
	2	10/20/10	-0.2997	10/21/10	-3.8076	10/22/10	0.5208
	3	10/21/10	-3.8076	10/22/10	0.5208	10/25/10	-0.4145
	4	10/22/10	0.5208	10/25/10	-0.4145	10/26/10	-3.2258
TargetDate	5	10/25/10	-0.41451	10/26/10	-3.22581	10/27/10	-3.65591
		Forecast%	-3.8622	Forecast%	-0.8491	Forecast%	-0.8383



UBA Actual/Forecast's Chart

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