The Journal of
Mathematics and Computer Science

Available online at
http://www.TJMCS.com

The Journal of Mathematics and Computer Science Vol. 4 No.2 (2012) 227 - 236

Predicting Changes in Stock Index and Gold Prices to Neural Network Approach

Ali ghezelbash

teacher.ghezelbash@yahoo.com

Received: January 2012, Revised: April 2012
Online Publication: June 2012

Abstract: This paper presents a study of artificial neural networks for use in stock price prediction. The data from an emerging market, Tehran's Stock Exchange (T.S.E), are applied as a case study. Based on the rescaled range (R/S) analysis, the behavior of stock price has been studied. R/S analysis is able to distinguish a random series from a non-random one. It is used to detect the long-memory effect in the TEPIX time series. It is shown that the behavior of stock price is non-random and short-term prediction of the TEPIX is possible, and modeling of stock price movements can be done.

A multilayer perceptron (M.L.P) neural network model is used to determine and explore the relationship between some variables as independent factors and the level of stock price index as a dependent element in the stock market under study over time. The results show that the neural network models can get better outcomes compared with parametric models like regression and others traditional statistical techniques. Our test also shows that useful predictions can be made without the use of extensive market data or knowledge, and in the data mining process, neural networks can explore some orders which hide in the market structure.

Keywords: stock price index, multilayer perceptron, Backpropagation, parametric models

I. Introduction

People tend to invest in common stock because of its high returns over time. Stock markets are affected by many highly interrelated economic, social, political and even psychological factors, and these factors interact with each other in a very complicated manner.

Therefore, it is generally very difficult to forecast the movements of stock markets. Refenes et al [1] indicate that conventional statistical techniques for prediction have reached their limitation in applications with nonlinearities in the data set. Artificial neural networks (A.N.N), a computing system containing many simple nonlinear computing units as neurons interconnected by links, is a well-tested method for financial analysis on the stock market. Neural networks have been shown to be able to decode nonlinear financial time series data.

Examples using neural networks in equity market applications include recognition of patterns in trading charts, rating of corporate bonds, estimation of the market price of options and futures, and the indication of trading signals of buying and selling, etc. Feed-forward

Back-propagation neural networks are the most commonly used networks and meant for the widest variety of the efficiency of the markets, returns follow a random walk. If this hypothesis comes true, it will make all prediction methods worthless.

Research on Iranian studies for business excellence in Tehran's Stock Exchange, like Fadai Nejad [2], and Abdoh Tabrizi and Jouhari [3]and Namazi and Shoustarian [4] to be inefficient than the mature markets. In fact, even the stock price movements of U.S [5] and Japan [6] have been shown to conform only the weak from of the efficient market hypothesis.

The second school's view is the so-called fundamental analysis. It looks in depth at the financial conditions and operating results of applications in theis field of science.

This paper shows that without the use of extensive market data useful and proper prediction can be made. It begins with general discussion of the possibilities of common stock price forecasting in an emerging stock market, like Tehran's Stock Exchange (T.S.E). It is followed by a section neural network, subsequently, a section is devoted to a case study on the stock price Index in Tehran's Stock Exchange, pointing to the promises and problems of such an experiments.

In this paper, taking the output of the neural network, it has been implemented using MATLAB software.

II. The Stock Market Prediction

Prediction in stock market has been a hot research topic for many years. Generally, there are four schools of thought in terms of the ability to profit from the stock market. The first school believes that no investor can achieve above average trading advantages based on the

historical and present information. The major theories include the Random Walk Hypothesis and the Efficient Market Hypothesis [7].

The Random Walk Hypothesis states that prices on the stock occurs without any influence by past prices. The Efficient Market Hypothesis states that price on the stock occur without any influence by past prices. The Efficient Market Hypothesis states that the market fully reflects all of the freely available information and prices are adjusted

fully and immediately once new information becomes available.If this is true then there should not be any benefit for prediction, because the market will react and compensate for any action made from these available information.

The second school suggests that in the actual market, some people do react to information immediately after they have received the information while other people wait for the confirmation of information.The waiting people do not react until a trend is clearly established. Because of a specific company and the underlying behavior of its common stock.The value of a stock is established by analysing the fundamental information associated with the company such as accounting, competition, and management.

The third school's view is technical analysis, which assumes the stock market moves in trends and these trends can be captured and used for forecasting. It attempts to use past stock price and volume information to predict future price movements. The technical analyst believes that there are recurring patterns in the market behavior that are predictable. They use such tools as charting patterns, technical indicators, and specialized techniques like Elliot Waves and Fibonacci series [8]. Indicators are derived from price and trading volume time series. Unfortunately, most of the techniques used by technical analysts have not been shown to be statistically valid and many lack a rational explanation for their use.

The fourth school's view is dynamic systems and chaotic behavior of stock price. From this standpoint, stock price movements have a very complex and nonlinear relations to some variables which advanced mathematical modeling of its can be done [9]. One of the challenges of modern capital market analysis is to develop theories that are capable of explaining the movements in asset prices and returns. The study of stock market has led financial economists to apply statistical techniques from chaos theory for analysing stock market data. Based on these new techniques, recent empirical studies document nonlinearities in stock market data.

Our main result is that stock price structure is many complex and neural network model is appropriate for capturing all the nonlinear dynamic relationships in Tehran's stock Exchange.

III. Neural Network

There are different types of networks, but all of them are composed of two components: Set of nodes and connection between nodes (edges) there are different types of networks. In between there is a network that is considered node as an artificial neuron. In terms of, it's such networks are called Artificial Neural Network Or briefly ANN. In fact an artificial neuron is a Computational model that of neurons in real nervous man is inspired. Natural neurons, receive their input through synapses.

These synapses are located on Dendrites or nerve membrane. In a real nerve, Dendrites are changing the amplitude of the received pulses of this type will not change during the same time. In terms, be learned by nerve. If the received signal is strong enough (A higher threshold is), Active nerve and the signal is spread in during the Axon, This signal can also turn into a more synapses and trigger other nerves. When modeling the nerves, regardless of its complexity is and Value is given only to the basic concepts. Otherwise, the modeling approach will be very difficult. A simple look at, Model of a nerve should include the input which in the role of Synapses can duty of. The inputs are multiplied by the weight of to determine signal strength. Ultimately decides a mathematical operator whether neurons can be activated or not and if the answer is positive, output level highlights. So artificial neural network using a simplified model of actual nerve deals with information processing. Given this description, we can describe a simple model of a neuron (a node in Artificial Neural Network) proposed. This model is shown in Figure 1. Apart from the simplification applied, the main difference this model with reality that in real network inputs is time signals, however, in this model the real numbers, are input.

Various functions can be used for thresholding. Among the most famous of these functions can be functions such as arcsin,arctan and sigmoid pointed. These functions must be continuous and smooth and are derived also number of input nodes may range. But with the rise of these nodes, clearly the difficulty of determining the weight. So we must look for ways to solve this issue. Determine the optimal weights and the values they mainly do is recursively. Therefore using the rules and data network trained using the learning capability of the network, various algorithms are proposed, all of which tried to approach by the network output and expected output are ideal.

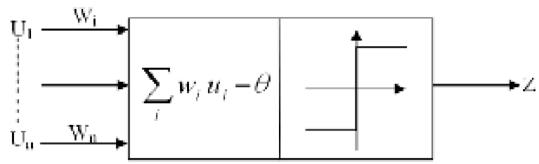

Figure 1
a simplified mathematical model of the actual nerve

Although the model neuron is the most important key points in the neural network performance but how to establish connections and layout (topology) in the network is very important. Should be noted that topology of the human brain is so complex that it can not be used as a model forthe neural network. because model we use a simple model is that while the arrangement of the brain makes use many elements. One of the simplest and yet most efficient arrangement proposed for use in modeling real neural models MultiLayer Perceptron or MLP. Consists of an input layer, one or more hidden layers and an output layer. In this structure, all neurons of one layer connected to all neurons after layer. This arrangement makes so complete a network of connections.

Figure 2 shows the schema of a three layer MLP. Can easily be deduced that the number of neurons per layer, other layers are independent of the number ofneurons. It is important to note that In Figure2, each circle is the sum of accumulation and thresholding (through thenonlinear sigmoid function) is. In fact, the solid circle in Figure2, is a model of collector and thresholding block shown in Figure 1, that to facilitate the display, to this form is shown.

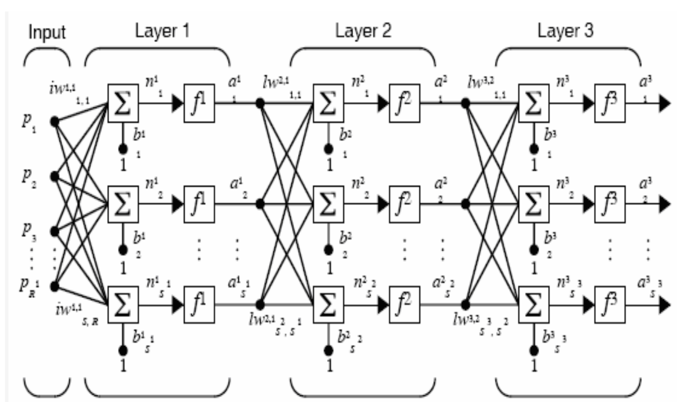

Figure (2) 3-layer perceptron networks with n neurons in each layer

Considering the output of ith nerve (in the last layer) can be showed as formula (1)

$$O_{\mathrm{i}} = \mathrm{sgm}\left(\sum_{\mathrm{m}} \mathrm{sgm}\left(\sum_{\mathrm{l}} \mathrm{x_i} \mathrm{w}_{\mathrm{lm}}^{\mathrm{h}}\right) \mathrm{w}_{\mathrm{mi}}^{\mathrm{o}}\right) \tag{1}$$

Where, O and h respectively represent the hidden layer and output layer and w is the weight of the layers. sgm is also sigmoid function which is defined as.

$$sgm(x) = \frac{1}{1+e^{-x}} \quad (2)$$

For training network and weigh improve to achieve a significant error, there are so many ways. One of the most famous of these methods is the error back propagation algorithm, which is described below.

Error back propagation algorithm:

The propagation error method is of methods with the supervisor. This means that the input samples are labeled and their expected output of each is known before.

The network output is compared with the ideal output and the network error is calculated. In this algorithm, the first assumption isthat network weights arechosen randomly. Network output is calculated at each step and in terms rate its differences with optimal output, the weights are corrected. Until finally, this error can be Minimum. The error back propagation algorithm, the function of each nerve stimulation as a weighted sum of inputs to the nerve is considered. Thus, assuming that w corresponding weights between input layer and the layer is next, Can write:

$$A_{j\,(\bar{x},\bar{w})=} \sum_{i=0}^{n} x_i w_{ji} \quad (3)$$

Can be seen clearly that, the output function nerve stimulation only inputs and corresponding weightsdepend on. Assuming that the output function, is sigmoid, jth nerve output can be wrote the following:

$$O_j(\bar{x},\bar{w}) = sgm\left(A_j(\bar{x},\bar{w})\right) = \frac{1}{1+e^{A_j(\bar{x},\bar{w})}} \quad (4)$$

With Accuracy in relation (4) we find that weights can be changed to change the output.

As mentioned before that the purpose of training process to achieve optimal output (or near optimal) is. Therefore for each neuron must first define the error function, the error of the difference between the actual network output and expected outputis obtained as follows:

$$E_j\left(\bar{x},\bar{w},d_j\right) = \left(O_j(\bar{x},\bar{w}) - d_j\right)^2 \quad (5)$$

IV. Design of Neural Network

The developer must go through a period of trial and error in the design descions before coming up with a satisfactory design. The design issues in neural networks are complex and are the major concern of system developers. Designing a neural network consists of:

• Arranging neurons in various layers.

• Deciding the type of connections among neurons for different layers, as well as among the neurons within a layer.

• Deciding the way a neuron receives inputs and produces output.

• Determing the strength of connection within the network by allowing the network learn the appropriate values of connection weights by using a training data set.

The process of designing a neural network is an iterative process.

V. Financial time series forecasting with neural networks

Based on the technical analysis, past information will affect the future. So, there should be some relationship between the stock prices of today and future. The relationship can be obtained through a group of mapping of constant time interval.

Assume that ui represents today's price, γi represents the price after ten days. If the prediction of a stock price after ten days could be obtained using today's stock price, then there should be a functional mapping ui to γi, where

$$\nu_i = \Gamma_i(u_i) \qquad (6)$$

More generally, U which consists of more information in today's price could be used in function Γ( ). Neural networks can simulate all kinds of functions, so they also can be used to simulate this Γ( ) function.

The U is used as the inputs to the neural network.

There are three major steps in the neural network based forecasting proposed in this research: preprocessing, architecture, and postprocessing.

In preprocessing, information that could be used as the
inputs and outputs of the neural networks are collected. These data are first normalized or scaled in order to reduce the fluctuation and noise.

In architecture, a variety of neural network models that could be used to capture the relationships between the data of inputs and output are built, Different models and configurations using different training and fore casting data sets are experimented. The best models are then
selected for use in forecasting based on such meseaures as out-ofsample hit rates. Sensitive analysis is then performed to find the most influential variables fed to the neural network. Finally, in postprocessing, different trading strategies are applied to the forecasting results to maximize the capability of the neural network prediction.[10]

VI. Measurements of neural network training

The Normalized Mean Squared Error (NMSE) is used as one of the measures to decide which model is the best. It can evaluate and compare the predictive power of the models. The definition of NMSE is:

$$NMSE = \frac{\sum_k \left(X_k - \hat{X}_k\right)^2}{\sum_n (X_k - \bar{X}_k)^2} \qquad (7)$$

Where X_k and $\hat{X}_k$ represent the actual and predicted Value respectively, and $\bar{X}_k$ is the mean of X_k.
Other evaluation meseaure includes the calculation of the correctness of gradients.

NMSE is one of the most wildly used meseaurments. It represents the fit between the neural network predictions and the actual targets. We argue that NMSE is a very important signal for pattern recognition. direction.

VII. Something about prediction of TEPIX

The TEPIX is calculated on the basis of Iranian stocks. It is capitalization – weighted by Laspiers formula and has a base level of 100 as of 1990. It has only 21 years of history, so there are not enough fundamental data that could be used for forecasting. Besides, the T.S.E is considered a

young and speculative market, where investors tend to look at price movements, rather than the fundamentals. Due to the high returns in emerging markets, investors are attracted to enhance their performance and diversify their portfolios.
In this paper, a combined method includes technical analysis and fundamental analysis applied to predict the behavior of stock price index. Neural networks are trained to approximate the market values which may reflect the thinking and behavior of some stock market traders.Forecasting of stock indices is to find the nonlinear dynamic regularities between stock prices and historical indices together with trading volumes time series. Due to the nonlinear interaction among these variables, it is very difficult to find the regularities but the regularities do exist. This research is aimed to find the hidden relationship between these indicators and future TEPIX through a neural network model.
Different factors are used as the inputs to a neural network and the index of stock price is used to supervise the training process, in order to discover implicit rules governing the price movement of TEPIX. Finally, the trained neural network is used to predict the future levels of TEPIX. The technical analysis method is used commonly to forecast the TEPIX, buying and selling point, turning point, and the highest, lowest point, etc. Neural network could be used to recognize the patterns of the chart and the value of index.
There are two principal phases in neural network analysis! "learning" and "predicting". During the learning, or training, phase the network "learns" by adjusting the weights between it nodes. The input data must be presented to the network many times. Data are split into two files. The first is used to train the network and the second file (the recall set) is used as a test of the networks predictive ability. During the training phase the network weights are saved at many intervals and tested to see how well the network can predict outcomes using weights it has learned up to that point. Following thousands of iterations, convergence occurs and the best weights for each element of the network can be derived.

VIII. Data Normalization and pre-processing

The daily data from 2008 to 2011 are used to the first trial. Figure shows the graph of the TEPIX represented as logarithmic return in (I_{t+1}/I_t) for the defined period, where I_t is the index value noisy which markets forecasting very difficult. The inputs to the neural network models are:

1- Gold coin average change 2 weeks ago.
2- Gold coin average change 1 week ago.
3- U.S. Dollar exchange 2 weeks ago.
4- U.S. Dollar exchange 1 week ago.
5- T.S.E volume change 2 weeks ago.
6- T.S.E volume change 1 week ago.
7- Moving average of TEPIX 2 weeks ago.
8- Moving average of TEPIX 1 week ago.

The output of the neural network is stock price index, which shows the price level of the market.
In general, the stock price data have bias due to difference in name and spans. Normalization can be used to reduce the range of the data set to values appropriate for input to the activation function being used. The normalization and scaling formula is:

$$y = \frac{2x - (max + min)}{max\ -\ min} \tag{8}$$

Where x is the data before normalizing. y is the data after normalizing. Stock price index is normalized in the same scale. The outputs of the neural network will be rescaled back to the original value according to the same formula.

IX. Nonlinear analysis of the TEPIX data

Statistics characteristics of TEPIX series are analysed first before applying it to neural network models. Table 1 shows means, maximum, minimum, Variance, standard deviation, skewness, and kurtosis.

TABLE1
STATISTICS RESULTS OF TEPIX

Min	mean	max	stdev	var	skew	kurt
154	1822.7	2092	157.588	24833.9	0.170812	0.5028

The rescaled range analysis (R/S analysis) is able to distinguish a random series from a non-random series, irrespective of the distribution of the underling series. In this paper, it is used to detect the long- memory effect in TEPIX time series over a time period. The R/S ratio of R and standard deviation of the original time series can by estimated by the following empirial law:

$$R/S = N^H \qquad (9)$$

When observed for various N values For a value N, the Hurst exponent can be calculated by

$$H = \log (R/S) / \log(N) \qquad 0<H<1 \qquad (10)$$

The Hurst exponent H describes the probability that two
consecutive events are likely to occur. The type of series described by H = 0.5 is random, consisting of uncorrelated events. A value of H different from 0.5 denotes the observation that are not independent.
When $0.5<H<1$, H describes a presistent or trend- reinforcing which is characterized by long memory effects. The value of Hurst exponent for the TEPIX time series was found to be 0.87 which indicates a long- memory effects in the time series. Hence, there exist possibilities for conducting time series fore casting in the TEPIX data.According to

X. Conclusion:

Beale and Jackson [11], a neural network with one hidden layer can model any continuos function Depending on how good we want to approximate our function, we may need tent, hundreds, thousands, or
even more neurons. There are two formula which appeared in the discussion of neural network newsgroups:

No- of- hidden-nodes= $\sqrt{input * output}$ (11)

No- of- hidden- nodes = In (No- of- nodes- in- previous-layer) (12)

We found the architecture of neural network based on NMSE of training and testing sets, which shows the best architecture is 8-3-1, that means we must have three hidden layer. Our results shown in table 2.

TABLE2
THE NEURAL NETWORK MODEL

Architecture	Learning rate α	NMSE
8-2-1	0.005	0.231175
8-3-1	0.005	0.178895
8-4-1	0.005	0.206726
8-5-1	0.005	0.252342

the network was run for numerous times, each time omitting one after omitting a variable are the same or even better it can be inferred that this variable probably does not contribute much to producing the outcome. Our results are shown in Table 3.

TABLE3
SENSITIVE ANALYSIS RESULTS

Architecture	α	NMSE
a) 8-3-1	0.005	67%
b) 6-3-1	0.005	85%
c) 6-3-1	0.005	78%
d) 6-3-1	0.005	75%

As in table is shown. In each condition two variables of the same group like (Gold, Moving Average, Exchange Rate, Volume) is omitted and the effect this change is calculated. The descent gradient shows all variables have effect on the results of neural network. The performance of neural network for prediction of TEPIX is shown in figure4. As shown in Figure 4. the neural network has a good performance for predicting the TEPIX in testing set.

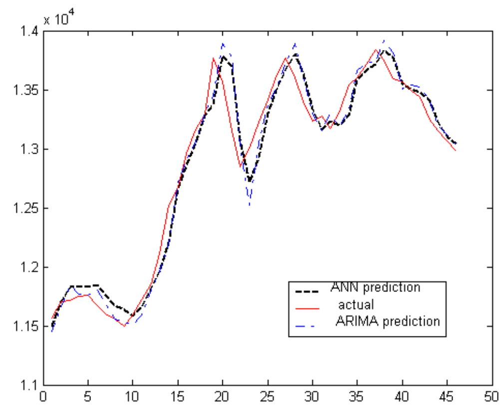

Figure 3:
The comparison of actual and desired results of TEPIX

References:

[1] Refenes, A.N; A.Zaparanis and G.Francis,"Stock performance modeling using neural networks: a comparative study study with regression models"; 1994; Neural networks; No 5; pp. 691-670

[2] Fadai nejad. M.I; "Stock market efficiency: some misconceptions"; 1994; Journal Financial Research; Vol. 1; No2.

[3] Abdoh Tabrizi.H, H. Jouhare; "The Investigation of Efficiency of stock price index of T.S.E ";1996;Journal of Financial Research; vol.13, No 11 & 12.

[4] Namazi. M; Z. Shoushtarian; "A Review of Test on the weak form of Efficient market hypothesis"; 1996; Journal of Financial Research; Vol. 13; No 11 and 12.

[5] Fama, E.F; "The behavior of stock market prices"; 1965; Journal of Business.

[6] Ang- J.S; R.A.Pohlman; "A note on the price behavior of Far Eastern stock"; 1978; Journal of International Business Studies.

[7] Peters. E; Chaos and orders in the capital markets: A new view of cycles, prices, and market volatility; 2001; john Wiley & sons.

[8] Plummer. T; Forecasting Financial markets: A Technical Analysis and the Dynamic of price; 1991; John Wiley; N.Y.

[9] Abdoh Tabrizi. H; M. Gonabudi; "Debate in validitation of Financial models;" 1996; Accountant No 115.

[10] Hornik. K; M. Stinchcobe and H. white; "Multilayer feed forward networks are universal approximators"; 1989; Neural Networks; 2(5); pp. 359-366.

[11] Beale. R; T. Jackson; Neural computing: An Introduction; 1990; Adam Hilger.