Stock Price Prediction by Artificial Neural Networks: A Study of Tehran's Stock Exchange (T.S.E)

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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

1. 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, which adequately describe the characteristics of the stock markets [2]. 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 these hypothesis come true, it will make all prediction methods worthless.

The research done here would be considered a violation of the above two hypothesis for short- term trading advantages in, Tehran's Stock Exchange, which is considered by some Iranian researchers such as Fadai Nejad [4], and Abdoh Tabrizi and Jouhari [5]and Namazi and Shoustarian [6]to be inefficient than the mature markets. In fact, even the stock price movements of U.S [7] and Japan [8] 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 these 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. At last, a conclusion which also discusses areas for future research is included at the end of the paper.

2- 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 [3].*** 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. 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 [9]. 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 [10]. 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.

3- Neural Network and its Usage in Stock Price Prediction

3.1- Neural Network

A neural network is a collection of interconnected simple processing elements (P.E). Every connection of neural network has a weight attached to it. Artificial neural network is a system loosely modeled on the human brain. The field goes by many name, such as connectionism, paralleled distributed processing, neurocomputing, natural intelligent systems, machine learning algorithms, and artificial neural networks. It is an attempt to simulate within specialized hardware or sophisticated software, the multiple layers of simple processing elements called neurons. Each neuron is linked to certain of its neighbors with varying coefficients of connectivity that represent the strengths of these connections. Learning is accomplished by adjusting these strengths so cause the overall network to output appropriate results. The backpropagation algorithm has emerged as one of the most widely used learning procedures for multilayer networks. The basic unit of neural networks, the artificial neurons, simulates the four basic functions of natural neurons. All natural neurons have four basic components, which are dendrites, soma, axon and synapses. Basically, a biological neuron receives inputs from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then output the final result. Artificial neurons are much simpler than the biological neuron; the figure1. shows the basics of artificial neurons.

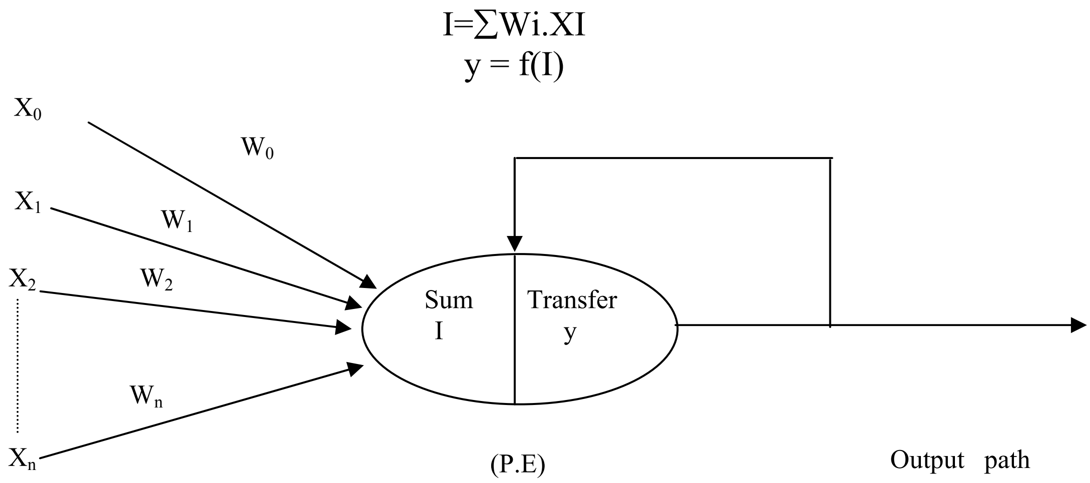


Figure1. Simple artificial neural network

The typical backpropagation neural networks usually has an input layer, some hidden layers and an output layer.Figure2 shows a one- hidden layer neural network.The units in the network are connected in a feed forward manner, from the input layer to the output layer. The weights of connections have been given initial values. The error between the predicted output value and the actual value is backpropagated through the network for the updating of the weights. This method is proven highly successful in training of multilayered neural networks.The network is not just given reinforcement for how it is doing on a task. Information about errors is also filtered back through the system and is used to adjust the connections between the layers, thus improving performance. This a supervised learning procedure that attempts to minimize the error between the desired and the predicted outputs. [11]

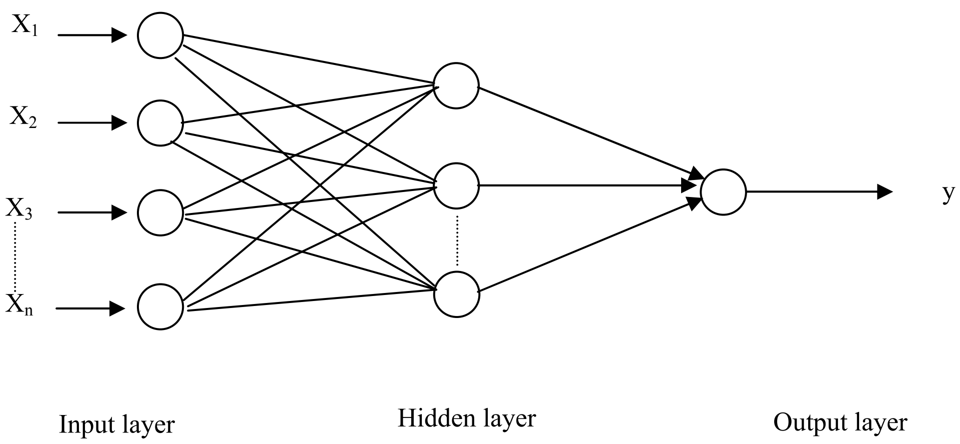


Figure2. A neural network with one hidden layer

The output value for a unit; is given by the following functions:

$$O_j = G\left(\sum_{i=1}^{m} w_{ij} x_j - \theta_j\right)$$

where xi the output value of ith unit in a previous layer, w_{ij}, is the weight on the connection from the ith unit, θ_j is the threshold, and m is the number of units in the previous layer. The function G( ) is a sigmoid hyperbolic tangent function:

$$G(Z) = \tanh(Z) = \frac{1 - e^{-Z}}{1 + e^{-Z}}$$

G( ) is a Commonly used activation function for time series prediction in back propagation [12].

3.2- 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.

3.3- 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 u_i represents today's price, γ_I 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 u_i to γ_I, where

$$v_i = \Gamma_i(u_i)$$

Using all (ui, vi) pairs of historical data a general function Γ( ) which consists of Γi( ) could be obtained.

$$\nu = \Gamma(u)$$

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- of-sample hit rates. Sensitive analysis is then performed to find the most influential variables fed to the neural network. Finally, in post processing, different trading strategies are applied to the forecasting results to maximize the capability of the neural network prediction [13].

3.4- 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

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

Where Xk and $\hat{X}_k$ represent the actual and predicted Value respectively, and $\overline{X}_k$ is the mean of Xk.
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.

3.5- Neural Network Topologies

The arrangement of neural processing unit and their interconnections can have a profound impact on the processing capabilities of the neural networks. In general, all neural networks have some set of processing units that receive inputs from the outside world, which we refer to appropriately as the “input units”. Many neural networks also have one or more layers of “hidden” processing units that receive inputs only from other processing units. A layer or “slab” of processing units receives a vector of data or the outputs of a previous layer of units and processes them in parallel. The set of processing units that represents the final result of the neural network computation is designated as the “output units”. There are three major connection topologies that define how data flows between the input, hidden, and output processing units. These main categories- feed forward, limited recurrent, and fully recurrent networks- which we are used the feed- forward networks.

Feed – forward networks are used in situations when we can bring all of the information to bear on a problem at once, and we can present it to the neural network. In this type of neural network, the data flows through the network in one direction, and the answer is based solely on the current set of inputs.

In Figure 3, we see a typical feed- forward neural network topology. Data enters the neural network through the input units on the left. The input values are assigned to the input units as the unit activation values. The output values of the units are modulated by the connection weights, either magnified if the connection weight is positive and greater than 1.0, or being diminished if the connection weight is between 0.0 and 1.0. If the connection weight is negative, the signal is magnified or diminished in the opposite direction.

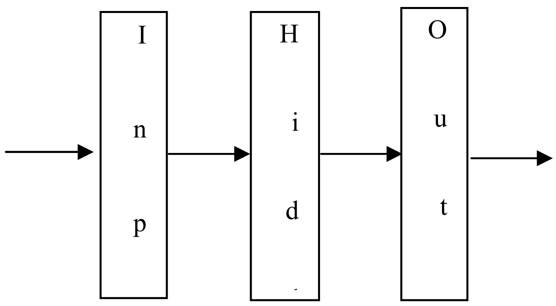


Figure 3: Feed- forward neural networks.

Each processing unit combines all of the input signals into the unit along with a threshold value. This total input signal is then passed through an activation function to determine the actual output of the processing unit, which in turn becomes the input to another layer of units in a multi- layer network. The most typical activation function used in neural networks is the S- shaped or sigmoid (also called the logistic) function. This function converts an input value to an output ranging from 0 to 1. The effect of the threshold weights is to shift the curve right or left, thereby making the output value higher or lower, depending on the sign of the threshold weight. As shown in Figure 3, the data flows from the input layer through zero, one, or more succeeding hidden layers and then to the output layer. In most networks, the units from one layer are fully connected to the units in the next layer. However, this is not a requirement of feed- forward neural networks. In some cases, especially when the neural network connections and weights are constructed from a rule or predicate form, there could be less connection weights than in a fully connected network. There are also techniques for pruning unnecessary weights from a neural network after it is trained. In general, the less weights there are, the faster the network remember that “feed- forward” is a definition of connection topology and data flow. It does not imply any specific type of activation function or training paradigm.

3.6- Neural Network Models

The combination of topology, learning paradigm (supervised or non-supervised learning), and learning algorithm define a neural network model. There is a wide selection of popular neural network models. For data mining, perhaps the back propagation network and the Kohonen feature map are the most popular. However, there are many different types of neural networks in use. Some are optimized for fast training, others for fast recall of stored memories, others for computing the best possible answer regardless of training or recall time. But the best model for a given application or data mining function depends on the data and the function required.

A back propagation neural network uses a feed- forward topology, supervised learning, and the (what else) back propagation learning algorithm. This algorithm was responsible in large for the reemergence of neural networks in the mid 1980s.

Back propagation is a general purpose learning algorithm. It is powerful but also expensive in terms of computational requirements for training. A back propagation network with a single hidden layer of processing elements can model any continuous function to any degree of accuracy (given enough processing elements in the hidden layer). There are literally hundreds of variations of back propagation in the neural network literature, and all claims to be superior to “basic” back propagation the other. Indeed, since back propagation is based on a relatively simple form of optimization known as gradient descent, mathematically astute observers soon proposed modifications using more powerful techniques such as conjugate gradient and Newton’s methods. However, “basic” back propagation is still the most widely used variant. Its two primary virtues are that it is simple and easy to understand, and it works for a wide range of problems.

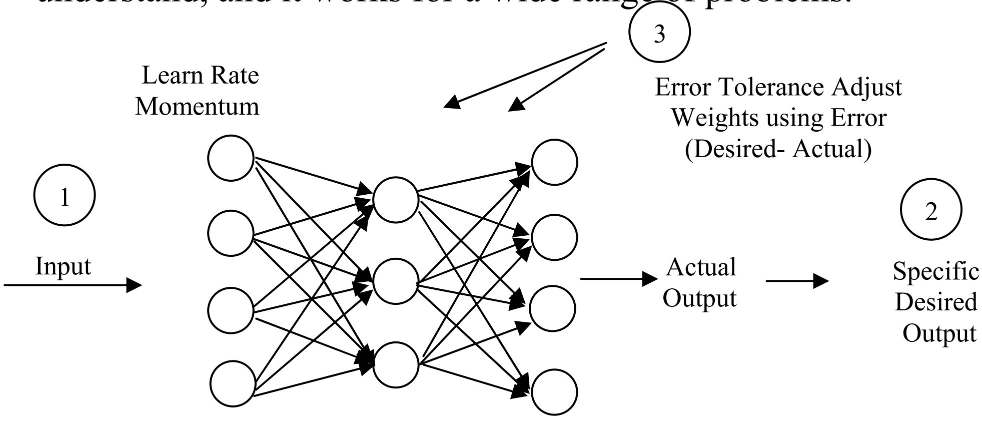


Figure 4. Back propagation network

The basic back propagation algorithm consists of three steps (see Figure 4). The input pattern is presented to the input layer of the network. These inputs are propagated through the network until they reach the output units. This forward pass produces the actual or predicted output pattern. Because back propagation is a supervised learning algorithm, the desired outputs are given as part of the training vector. The actual network outputs are subtracted from the desired outputs and an error signal is then the basis for the back propagation step, whereby the errors are passed back through the neural network by computing the contribution of each hidden processing unit and deriving the corresponding adjustment needed to produce the correct output. The connection weights are then adjusted and the neural network has just "learned" from an experience.

Back propagation is a powerful and flexible tool for data modeling and analysis suppose you want to do linear regression. A back propagation network with no hidden units can be easily used to build a regression model relating multiple input parameters to multiple outputs of dependent variables. This type of back propagation network actually uses an algorithm called the delta rule, first proposed by Widrow and Hoff.

Adding a single layer of hidden units turns the linear neural network into a nonlinear one, capable of performing multivariate logistic regression, but with some distinct advantages over the traditional statistical technique. Using a back propagation network to do logistic regression allows you to model multiple outputs at the same time. Confounding effects from multiple input parameters can be captured in a single back propagation network model. Back propagation neural networks can be used for classification, modeling, and time- series forecasting. For classification problems, the input attributes are mapped to the desired classification categories. The training of the neural network amounts to setting up the correct set of discriminate functions to correctly classify the inputs. For building models of function approximation, the input attributes to correctly classify the inputs. This could be a single output such as a pricing model, or it could be complex models with multiple outputs such as trying to predict two or more functions at once.

Two major learning parameters are used to control the training process of a back propagation network. The *learning rate* is used to specify whether the neural network is going to make major adjustments after each learning trial or if it is only going to make minor adjustments. *Momentum* is used to control possible oscillations in the weights, which could be caused by alternately signed error signals. While most commercial back propagation tools provide the most impact on the neural network training time an performance.

4- A Case Study on the Forecasting 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 ten 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.

4.1- Data Normalization and pre-processing

The daily data from 1995 to 1999 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

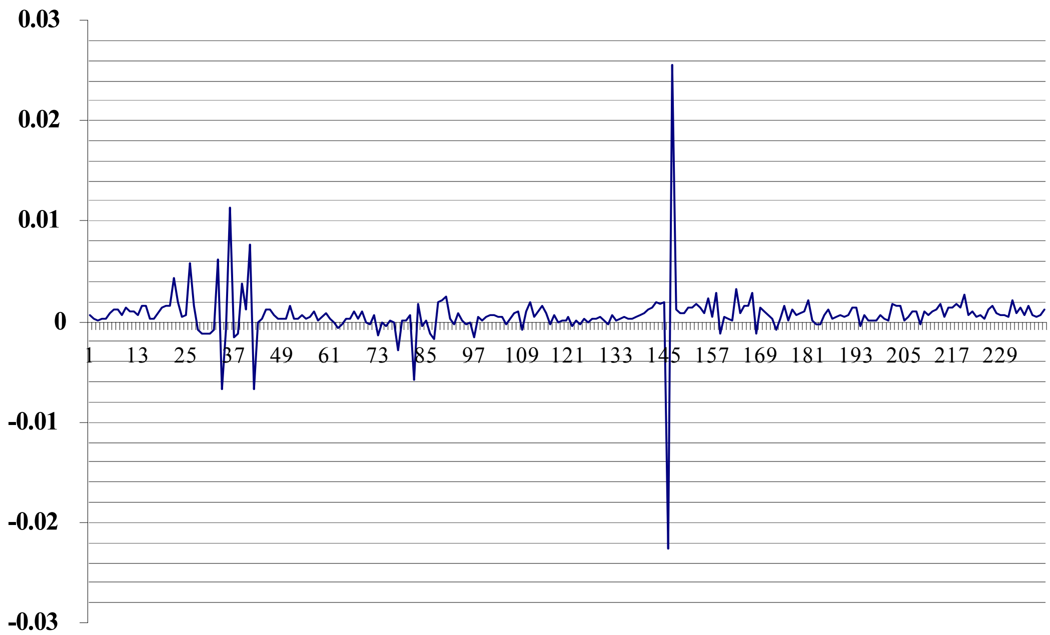
$$y = \frac{2x - (\max + \min)}{\max - \min}$$

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.



Figures. Logarithmic of TEPIX daily data

4.2- 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.

The high standard deviation of returns indicates that the risk in this market is indicates that the risk in this market is higher than developed market.

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.

Table 1. statistics results of TEPIX

Min	mean	max	stdev	var	skew	kurt
1540	**1822.77**	**2092**	**157.588**	**24833.9**	**0.170812**	**0.5028**

The R/S ratio of R and standard deviation of the original time series can by estimated by the following empirial law:

$$R/S = N^H$$

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

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

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.

4.3- Neural network model building

Historical data are divided into two parts: training and testing sets. The training set contains two- thirds of the collected data. A model is considered good if the error for out- of- sample testing is the lowest compared with the other models. If the trained model is the best one for testing, one can assume that it is a good model for future fore casting.

It is important not to have too many allow the neural neural network to learn by example only and not to generalize. According to Beale and Jackson [14], 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:

$$\text{No- of- hidden- nodes} = \sqrt{input * output}$$

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

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.

Able 2. Architecture of 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

Primary sensitive analysis is conducted for input variables. Models are built an attempt to discover which of these variables influence the output variable. As a rule of thumb to determine whether a variable is relevant, 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.

Table 3. 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 figure 6.

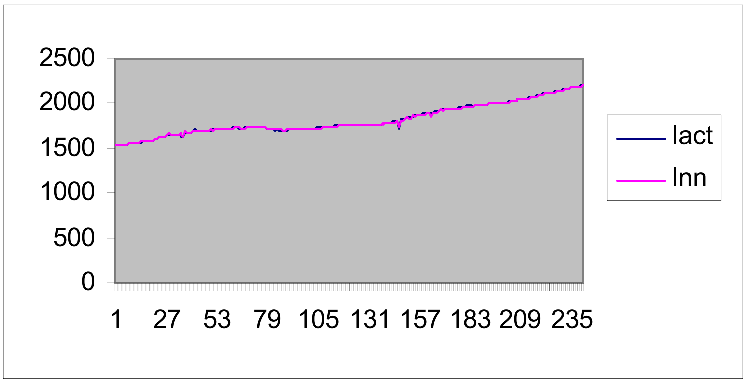


Figure 6. The comparison of actual and desired results of TEPIX

As shown in Figure 6. the neural network has a good performance for predicting the TEPIX in testing set.

4.4- Validation of the neural network

To compare the performance of an artificial neural network to linear regression, a regression equation was computed form the same data used for training the neural network. The equation then was used to predict stock price index from the same recall data set used to evaluate the neural network. The performance of each approach was tested to determine which tool is the better predictor. To test the significance of the difference in predictive ability of the two models, a matched sample pairs statistical procedure was used to test the hypothesis that the mean difference between the predictive between the model is zero (i.e. there is no difference between the predictive abilities of the two models). The p-value0.00089 is--, which is an evidence that the neural network out perform the regression model for predicting stock price index.

A procedure analogous to step- wise regression was used to investigate the significance of each determinant of models. The results show that neural network has best performance for predicting stuck price network has was significantly better able to explain the relationship between Inputs and output.

In analysing ongoing relationships between Inputs and outputs, neural network has three primary advantage over regression analysis:

1. Neural network development does net require knowledge of underlying relationships between the input and output variables (both linear and non- linear). Since the network "learns" relationships hidden in the data. These complex relationships are discovered and automatically assimilated into the weights connecting the nodes of the network. These weights contain the "learned information" from the network training phase and are analogous to regression coefficients.
2. The associative abilities of neural networks make them more robust to missing and inaccurate data, since the knowledge of relationships between variables is distributed across numerous network connections. Regression, on the other hand, cannot tolerate missing data and works poorly with inaccurate data since all relation- ship knowledge is stored in a single beta coefficient.
3. Neural networks performance is not diminished by the multi- collinearity problem of regression analysis- Non- standard conditions, violations of assumptions, high influence points, and transformations can all be handled by the neural networks.

5.conclusion and Future Research

This paper reports an empirical work which investigates the usefulness of artificial neural networks in fore casting the TEPIX. The performance of several backpropagation neural networks applied to the problem of predicting the TEPIX stock market index was evaluated. The delayed index levels and some technical indicators and fundamental elements of macroeconomics were used as the inputs of the neural networks, while the current index level was used as a output. With the prediction, significant power.

The significance of this research is as follows:

1- It shows that useful prediction could be made for TEPIX without the use of extensive.

2- It shows how annual return could be achieved by using the proposed model.

3- To improve neural network's capabilities, a mixture of technical and fundamental factors as inputs over different time period is used.

The characteristics of emerging market such as Tehran's stock exchange should be further researched to facilitate better market using neural networks. The forecasting results can then be applied to the trading of index linked stocks under consideration of the transaction costs.

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