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Stock Price Prediction of the Most Profitable Stock Exchange in the Asia During the Global Financial Crisis: A Comparative Study of Tehran Stock Exchange

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ABSTRACT
The purpose of this study is to provide a useful model for predicting the stock prices of companies listed in the Tehran Stock Exchange (TSE) during the Global Financial Crisis (GFC). Linear and exponential regression method and Artificial Neural Networks (ANNs) were used for this purpose. Then a comparison was done between the methods to determine the most effective of them for predicting the stock prices in the TSE. In this study, the stock prices were modelled by using the variables of the growth rate of industrial products, companies' net assets, inflation, oil prices, earning per share and price ratio of dividends. The study uses a body of data from 250 companies in the years, 2008-2011. The results showed that the correlation coefficients for the linear and exponential regressions are equal to 30.5 and 35.1%, respectively and for ANNs, they are 86.041%. This shows the tangible superiority of ANNs for predicting stock prices compared to classical methods. This means that investors must use scientific methods to forecast stock prices instead of using traditional methods, especially during the GFC.

Key words: Linear and exponential regressions, artificial neural networks, stock price, Tehran stock exchange, global financial crisis

INTRODUCTION
Nowadays, investment is the basis of progress in all countries. An important characteristic of developed countries is that their money and capital market is active and dynamic. In any economic system, a group with more activity and proper savings can earn more for the future. Savings can have positive or negative effects on communities. If these savings are directed with a proper mechanism towards production lines, besides efficiency, they can make the investors to have great savings; also they will be useful for establishing investment projects in the economy. If this money enters unhealthy economic flows it will have some inappropriate effects on communities. The most important task in a country with huge volume of liquidity is to guide, absorb and create conditions in order to increase the efficiency of these monetary resources for the whole community. In this respect the "Stock Exchange" is one of the most important tool which helps absorb this liquidity. Buying and selling mechanisms in the stock market play an important role because the owners can participate in supplying finance resources to the industries of their countries (Manne, 1966). Owners of small capitals are not able to get good returns from their investment and the size of today's economy will not allow them to have the power to produce alone or to move the wheel of their communities' economy. But if an appropriate mechanism is used to collect these small assets,

high efficiency can be achieved by the communities. Therefore, stock exchange is the most important economic institution in developed countries and its operations is one of the key indicators of the socio-economic conditions of these countries (Sharma and Roca, 2012). Any insecurity in the stock market could lead to a huge economic crisis. To select the best portfolio of an investor; it is necessary get accurate information and analysis. Investors can get desired profits if they have sufficient information about the stock market. Stock exchanges also play a significant role in any capitalist economy. They provide a secondary market where investors can buy and sell shares under systematic conditions at fair and competitive prices. To do so, prediction of stock price can be of great interest to stockholders, because they will be able to get the required information for their investment (Majhi *et al*., 2007). Stock market prediction has been dominated by Classical methods (e.g., Time-Series and linear regression) for many decades (Kendall, 1953; Rashid, 2007; Widrow *et al*., 1994). Linear methods are easy to develop and implement. They are also relatively simple to understand and interpret. But the linear models have a specific limitation in predication of nonlinear problems. In recent years, in order to tackle these problems, Artificial Neural Networks (ANNs) have been employed to carry out a variety of tasks in science, industry and business (Ahmadian *et al*., 2012; Cao *et al*., 2005; Choudhry *et al*., 2012; Dai *et al*., 2012; Lorrentz *et al*., 2010; Moallem and Razmjooy, 2012). There are some evidences which demonstrate that the ANNs have a powerful capability in prediction (Enke and Thawornwong, 2005; Medeiros and Pedreira, 2001; Trinkle, 2005). The ANNs have the capability to work with input variables and accordingly to handle a huge amount of data (Chang *et al*., 2007). ANNs provide a promising alternative tool for stock market predictors (Hwarng, 2001; Medeiros and Pedreira, 2001; Zhang, 2001). As it was mentioned before, forecasting is one of the application of ANNs which is interesting for researchers (Armano *et al*., 2005; Bhattacharyya *et al*., 2002; Chang *et al*., 2005, 2006, 2007, 2009, 2012; Chang and Wang, 2006; Ely and Salehizadeh, 1999; Jarrett, 2009). In this content, forecasting of stock price is one of the most interesting matters among researchers, some of them are mentioned in the following publications (Zhang *et al*., 1998; Vellido *et al*., 1999; Kim and Han, 2000, Kanas, 2001; Kanas and Yannopoulos, 2001; Maasoumi and Racine, 2002; Black and McMillan, 2004; Jasic and Wood, 2004; Enke and Thawornwong, 2005; Rapach and Wohar, 2005; Pai and Lin, 2005; Kim, 2006; Tsang *et al*., 2007; Hassan *et al*., 2007; Wang, 2009; Chavarnakul and Enke, 2008; Hsu *et al*., 2009; Zhu *et al*., 2008; Zhang and Wu, 2009; Cao and Parry, 2009; Atsalakis and Valavanis, 2009; Ahangar *et al*., 2010; Lu, 2010; Arnold *et al*., 2011; Chang, 2011; Enke *et al*., 2011; Hsu, 2011; Wang *et al*., 2011; Chen and Sutcliffe, 2012; Liu and Wang, 2012; Liu *et al*., 2012). In fact, prediction of stock price is a really plus point which acts like a torch in the stressful and complicated situation of stock markets for managers, stockholders and researchers; especially during the Global Financial Crisis (GFC) the importance of this work is more interesting. The present study attempts to specify the best method of forecasting between ANNs and classical linear and exponential regression methods to determine stock price for companies listed in the TSE during the GFC.

ARCHITECTURE OF ANNs

Back propagation network: ANNs can be classified into several categories based on supervised and unsupervised learning methods and (I) a feed forward step and (II) a back propagation weight training step. A BPNN is a neural network that uses a supervised learning method and

Feed-Forward architecture. A BPNN is one of the most frequently utilized ANNs techniques for classification and prediction and is considered an advanced multiple regression analysis that can accommodate complex and non-linear data relationships (Jost, 1993). The output of a BPNN is compared with the target output and an error is calculated for each training iteration. This error is then back propagated to the Neural Network and utilized to adjust the weights, thereby minimizing the mean squared error between the network's prediction output and the target output (Yahyazadehfar *et al*., 2012). The most popular ANNs training algorithm for financial forecasting is the BPNN (Ahangar *et al*., 2010; Ahmadi, 1990; Atsalakis and Valavanis, 2009; Cao and Parry, 2009; Chang *et al*., 2009; Lee and Chiu, 2002; Lee and Chen, 2002; Lu, 2010; Olson and Mossman, 2003; Vellido *et al*., 1999; Yahyazadehfar *et al*., 2012; Wang *et al*., 2011; Zhang and Wu, 2009; Zhang *et al*., 1998) which has a simple architecture but a powerful problem-solving ability. BPNN is essentially a gradient steepest descent training algorithm. For the gradient descent algorithm, the step size, called the learning rate, must first be specified. The learning rate is crucial for BPNN since smaller learning rates tend to slow down the learning process before convergence while larger ones may cause network oscillation and may be unable to converge (Lu, 2010). The structure of BPNN contains three layers: Input, hidden and output layers as shown in Fig. 1.

Each layer contains n, m and K nodes denoted, respectively by circles. The node is also called neuron or unit. The neurons are connected by links, denoted by arrows and those arrows represent numerical weights. The w_{ij} is denoted as numerical weights between input and hidden layers and so is w_{jk} between hidden and output layers. The processing or the computation is performed in each node in the hidden and output layers. As for the number of layers and number of nodes, they will be further decided using design of experiment.

In the back propagation weight training the error function is defined as (Chang *et al*., 2009):

$$E = \frac{1}{2}\sum_{k=1}^{K} e_k^2 = \frac{1}{2}\sum_{k=1}^{K} (t_k - z_k)^2 \tag{1}$$

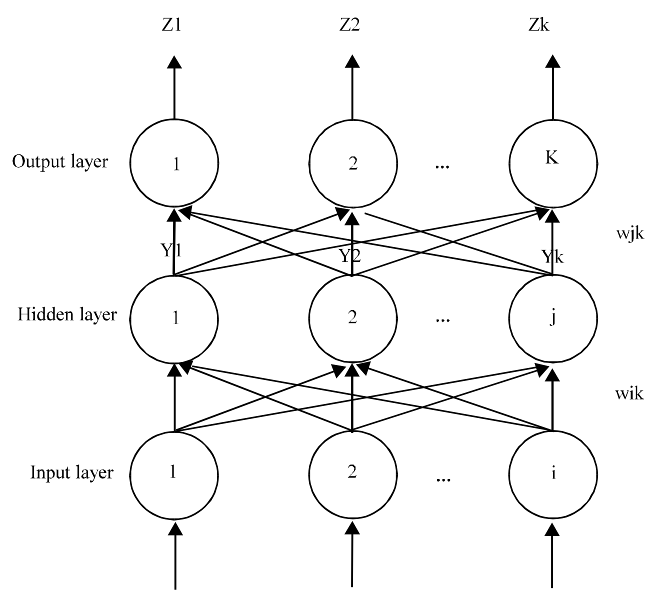

Fig. 1: Structure of back propagation neural network in the artificial neural networks

where, t_k is a predefined network output (or desired output or target value) and e_k is the error in each output node. The goal is to minimize E so that the weight in each link is accordingly adjusted and the final output can match the desired output. To get the weight adjustment, the gradient descent strategy is employed. In the link between hidden and output layers, computing the partial derivative of E with respect to the weight w_{jk} produces:

$$\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial z_k}\frac{\partial z_k}{\partial Y_k}\frac{\partial Y_k}{\partial w_{jk}} = -e_k\frac{\partial f(Y_k)}{\partial Y_k}y_i = -e_k f'(Y_k)y_i = -\delta_k y_i \tag{2}$$

where:

$$\delta_k = e_k f(Y_k) = (t_k - z_k) f(Y_k) \tag{3}$$

The weight adjustment in the link between hidden and output layers is computed by:

$$\Delta w_{jk} = \alpha y_i \delta_k \tag{4}$$

where, α is the learning rate, a positive constant between 0 and 1. The new weight herein can be updated by the following:

$$w_{jk}(n+1) = w_{jk}(n) + \Delta w_{jk}(n) \tag{5}$$

where, n is the number of iteration. Similarly, the error gradient in links between input and hidden layers can be obtained by taking the partial derivative with respect to w_{ij}:

$$\frac{\partial E}{\partial w_{ij}} = \left[\sum_{k=1}^{K}\frac{\partial E}{\partial z_k}\frac{\partial z_k}{\partial Y_k}\frac{\partial Y_k}{\partial y_i}\right].\frac{\partial y_i}{\partial X_j}.\frac{\partial X_j}{\partial w_{ij}} = -\Delta_j X_i \tag{6}$$

Where:

$$\Delta_j = f'(X_j) = \sum_{k=1}^{K}\delta_k w_{jk} \tag{7}$$

The new weight in the hidden-input links can be now corrected as:

$$\Delta w_{ij} = \alpha x_i \Delta_j \tag{8}$$

and:

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n) \tag{9}$$

Training the BPNN with many samples is a very time-consuming task. The learning speed can be improved by introducing the momentum term η usually; η falls in the range [0, 1]. For the iteration n, the weight change Δw can be expressed as:

$$\Delta w(n+1) = \eta \times \Delta w(n) + \alpha \times \frac{\partial E}{\partial w(n)} \tag{10}$$

Feed-forward neural network: Feed-forward ANNs are the most commonly used networks for a variety of applications in finance and accounting (Ahangar *et al*., 2010; Chang *et al*., 2009; Coakley and Brown, 2000; Lu, 2010; Yahyazadehfar *et al*., 2012) and have been widely used for financial forecasting due to their ability to correctly classify and predict the dependent variable. This network consists of neurons organized in three layers: Input layer, hidden layer and output layer. The neurons in the input nodes correspond to the independent that are believed to be useful for forecasting the dependent variable which corresponds to the output neuron. Neurons in the hidden layer are connected to both input and output neurons and are keys to learning the pattern in the data and mapping the relationship from input variables to the output variable. With nonlinear transfer functions, hidden neurons can process complex information received from input neurons and then send processed information to the output layer for further processing to generate forecasts (Yahyazadehfar *et al*., 2012).

Accordibg to Fig. 1 it is assumed that each input factor in the input layer denoted by x_i, y_j and z_k represent the output in the hidden layer and the output layer, respectively. And, y_j and z_k can be expressed as follows (Chang *et al*., 2009):

$$y_i = f(X_j) = f\left(w_{oj} + \sum_{i=1}^{I} w_{ij} x_i \right) \tag{11}$$

and:

$$z_k = f(Y_k) = f\left(w_{ok} + \sum_{j=1}^{J} w_{jk} y_j \right) \tag{12}$$

where, the w_{oj} and w_{ok} are the bias weights for setting threshold values, f is the activation function used in both hidden and output layers and X_j and Y_k are the temporarily computing results before applying activation function f. In this study, a hyperbolic tangent sigmoid function is selected as the activation function:

$$a = \tan \text{sig}(n) = \frac{2}{1+\exp(-2n)} - 1 \tag{13}$$

The activation function f is also known as a squashing function. It keeps the cell's output between certain limits as is the case in the biological neuron. Figure 2 shows the activation function f introduces the non-linear effect to the network and maps the result of computation to a domain (-1, 1).

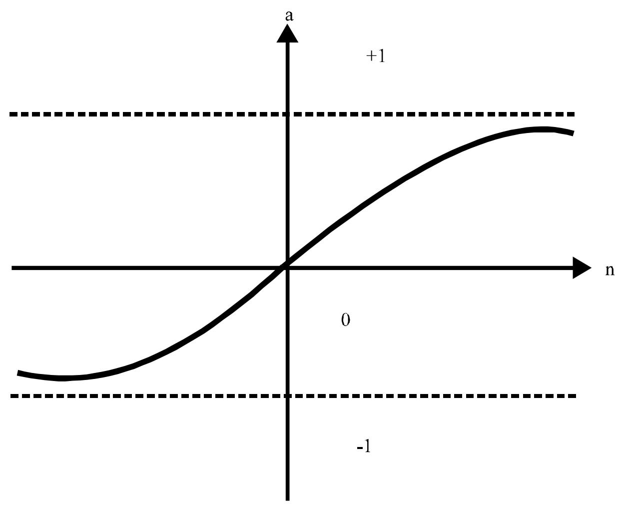

Fig. 2: Hyperbolic tangent sigmoid transfer function; a perceptron's activation functions

MATERIALS AND METHODS

Sample: With regard to the subjects, this research work attempts to present a model for predicting stock prices by analyzing the factors affecting stock prices of the companies in the TSE. The group consists of companies which have one or more attributes in common (financial and economic variables), all of which are of interest to the researchers. To ascertain the true prediction, the total population is used. Although, this type of research is time consuming it is accurate. This research is carried out in order to predict the stock price. Thus, the total study population was considered as the companies admitted in the TSE. For this purpose the study used a body/set of data from 250 companies that were available (all active companies on the stock market). The numbers of data related between the year 2008 and 2011 were 1,000.

Data collection: Scientific databases, websites and other electronic resources will be used to collect the required information, data documents and financial statements of companies will be reviewed by going to the exchange and Central Bank library. And also, some part of the information (the set of variables) collected by interviewing stockbrokers.

Variables: To design an accurate model firstly, the influencing variables in the stock prices are identified and then are used them to design the model. Since supply and demand determines the price of stock, the supply and demand for securities was carried out by stock brokers, as well as identification of the information for buying and selling. Thus, by referring to stock brokers and consulting with them and also by reading the latest articles published in this regard, the following variables are selected as the most influential. Olson and Mossman (2003) showed that models with three to seven independent variables result in the best forecasts for the considered period. Based on this study if the echelon solution chooses more than eight independent variables, p-value criterion reduces to 4 or 3%. But if the echelon solution chooses only one or two variables, p-value criterion increases to 10% so that more variables can be included. These variables have been chosen.

Financial variables include: 1-Net Assets (NA) 2-Earnings per Share (EPS) 3-The Price to Earnings per Share (P/E).

Economic variables include: 1-Industrial Production Growth Rate (IPGR) 2-Inflation Rate (IR) 3-Oil Prices (OP).

Statistical analysis: Researchers have often used linear and exponential regression models to estimate a dependent variable by one or more independent variables. Linear and exponential regressions (Classical Regression) can be employed to estimate a set of time series. The average of financial and macro economic variables of identified resources in the beginning of each year are independent variables in these estimations. Dependent variables are the real output of the company in estimation model which depend on price data of all stocks in the sample. Dependent variables will be estimated using regression step method (OLS). All independent variables will be entered in the regression equation. The independent variables with p-values more than 5% will be omitted in estimation period and at last, a subset of independent variables will be chosen. The regression analysis data for the years of 2008 to 2011 with the amount of 1000 data will be entered in the SPSS 16 software. At first, in the neural network, with attention to inputs and outputs of data, a function will be made for inputs' and outputs' behavior. In fact, this function which is network architecture will make a relationship between inputs and outputs. In the next step, data on 250 companies from the years 2008 to 2010 will be considered as training set and thereafter network training and minimizing training error, data from 2011 will be used as a test suite. Then the data will be entered in the Excel software making a total of 1000. The MATLAB 7.3 software is used to build neural network architecture and find the most appropriate architecture (structure) with the trial and error method.

RESULTS

Stock market is dynamic, complicated and chaotic in nature (Tan *et al.*, 2005). Initially, in order to forecast stock prices by classical methods, regression analysis is used to determine the correlations of variables:

$$\begin{aligned} &H1: \rho \neq 0 \ sig<0.05 \ accept \\ &H0: \rho = 0 \ sig=0.05 \ reject \end{aligned} \tag{14}$$

Table 1 shows the correlation matrix of variables. Pearson Correlation is used to show the nature of the correlated independent variables. It was observed that the Industrial Production Growth Rate and Oil Price have a positive relation with Stock Price, such as Net Assets, Earnings per Share, Price to Earnings per Share, while Inflation Rate has a negative relation with Stock Price. A variable with a sig value of higher than 0.05 was acceptable for analysis. As such, the Earnings per Share is the only variable whose sig. is more than 0.05. Therefore, this variable

Table 1: Correlation Matrix of independent variables listed in the Tehran stock exchange

Variables	(SP)	(IPGR)	(NA)	(IR)	(OP)	(EPS)	(P/E)	Sig.
(SP)	1	.	.	.	.	.	.	0.000
(IPGR)	-0.055	1	.	.	.	.	.	0.195
(NA)	0.141	0.02	1	.	.	.	.	0.103
(IR)	0	0.816	-0.017	1		.	.	0.499
(OP)	-0.093	0.715	0.035	0.269	1	.	.	0.072
(EPS)	0.305	0.01	0.287	-0.025	0.016	1	.	0.000
(P/E)	0	-0.084	-0.034	-0.041	-0.102	-0.084	1	0.497

Significance in 5% level. SP: Stock price, NA: Net assets, EPS: Earnings per share, P/E: Price to Earnings per share, IPGR: Industrial production growth rate, IR: Inflation rate and OP: Oil prices

Table 2: Stepwise method for showing excluded variables in the regressions method

Variables	t	Sig.	Method
(IPGR)	-0.953	0.341	Stepwise (Criteria: Probability-of-F-to-enter <= 0.050, Probability-of-F-to-remove >= 0.100)
(NA)	0.914	0.361	
(IR)	0.127	0.899	
(OP)	-1.623	0.106	
(P/E)	0.418	0.676	

Significance in 5% level. Significance in 5% level. SP: Stock price, NA: Net assets, EPS: Earnings per share, P/E: Price to Earnings per share, IPGR: Industrial production growth rate, IR: Inflation rate and OP: Oil prices

Table 3: Correlation coefficient, regression squared and p-value of linear regression

					Change statistics				
Model	R	R square	Adjusted R square	Std. Error of the estimate	R square change	F change	df1	df2	Sig. F change
A	0 .305	0.093	0.089	5641.10087	0.093	25.440	1	248	0.000

R: Correlation coefficient, R-squared: Rregression squared, Df: Degree of freedom, p-value: Significant, α = 5%

Table 4: Standard and un-standardized coefficients, standard errror, t-test and p-value of linear regression of independent variable in the stepwise method

	Un-standardized coefficients				
Variables	B	Std. Error	Standardized coefficients beta	t	Sig.
EPS	0.020	0.004	0.305	5.044	0.000
(Constant)	4178.611	399.778		10.452	0.000

B: Un-standardized coefficients of regression, Std. Error: Standard error of the estimator, Beta: Standard coefficints of regression, t: T test, p-value: Significant, α = 5%

has a significant relationship with stock prices in the TSE. The authors have examined this correlation using some industries and the results indicated that correlation of all variables is acceptable. With consideration for all companies in the TSE, the significant index is acceptable only for EPS. Therefore, the Stepwise Method is used instead of the Enter Method to enter the variables in the SPSS Software. In Table 2 it is observed that the sig. of all variables, except EPS, were not acceptable since the sig. of other variables were more than 0.05. For Earnings per Share the sig is <0.05, so it is acceptable. Indeed, Table 2 confirms the results of Table 1. In the Linear and Exponential regressions the EPS is used but in the ANNs all variables are considered for prediction. This problem is one of the restrictions of the regression in the prediction of huge amounts of data.

Table 2 shows the stepwise method in entering the variables. It is observed that EPS is the only variable whose sig. is more that 0.05.

Linear regression analysis: The purpose of this part is to predict the stock prices of companies admitted in the TSE by using the linear regression and to provide a model for them.

In Table 3, the correlation coefficient which generally shows the intensity of the relation between the independent variables and dependent variable, is equal to 30.5%. The coefficient of determination is equal to 9.3% which represents the amount of variability (standard deviation) in the dependent variable (price) that is explained by the regression. Regression row displayed information on changes in the model. The significance level is 0.000 and smaller than 0.05 which indicates that the change does not occur accidentally.

In Table 4, the obtained coefficients of the linear regression and their meaningfulness are checked. It was observed according to the variable shown in Table 4, the sig. is smaller than

Table 5: Correlation coefficient, regression squared and p-value of exponential regression

R	R square	Adjusted R square	Std. error of the estimate	F	Sig.
0.351	0.123	0.120	0.836	34.897	0.000

R: Correlation coefficient, R-squared: Rregression squared, Df: Degree of freedom, p-value: Significant, α = 5%

Table 6: Standard and un-standardized coefficients, standard errror, T-test, and p-value of exponential regression of independent variable in the stepwise method

	Un-standardized coefficients				
Variables	B	Std. Error	Standardized coefficients beta	t	Sig.
EPS	3.504E-6	0.000	0.351	5.907	0.000
(Constant)	2852.415	169.073		16.871	0.000

B: Un-standardized coefficients of regression, Std. Error: standard error of the estimator, Beta: Standard coefficints of regression, t: T test, p-value: Significant, α = 5%

0.05. This suggests that the obtained coefficient is significant. Now, with regard to the above table, the linear regression equation is as follows:

$$Y = 4178.611+0.02\ X \tag{15}$$

In the above equation, Y equals the stock price and X is equal to earnings per share.

Exponential regression analysis: In this section, the discussions revolve around what the exponential regression model is and how it works.

In Table 5, the correlation coefficient generally shows the intensity of relation between the independent variable and dependent variable which is 35.1% for the EPS variable. The coefficient of determination is equal to 12.3% which represents the amount of variability (SD) in the dependent variable (stock price) is explained by the regression. As mentioned above, the table shows the validity of the model from a statistical perspective. The regression row displays information on changes in the model. Significance level is 0.000 and smaller than 0.05 which indicates that the change does not occur accidentally.

In Table 6, the obtained coefficients of the exponential regression and also their meaningfulness are checked. As it is observed, by considering the variable shown in Table 6 its sig. is smaller than 0.05. Now, according to the above table, the exponential regression equation is as follows:

$$Y = 2852.415 +3.504\ E\text{-}6LN\ (X) \tag{16}$$

In the above equation, Y equals the stock price and x is equal to earnings per share.

In the chart below linear regression and exponential curve can be observed. According to Fig. 3, the data distribution with regard to the regression line equation is observed.

Structure of ANNs in this study: The neural network used to predict stock prices is a network with three layers of the interlayer structure. The structure of each of these three layers is explained in the following (Fig. 4).

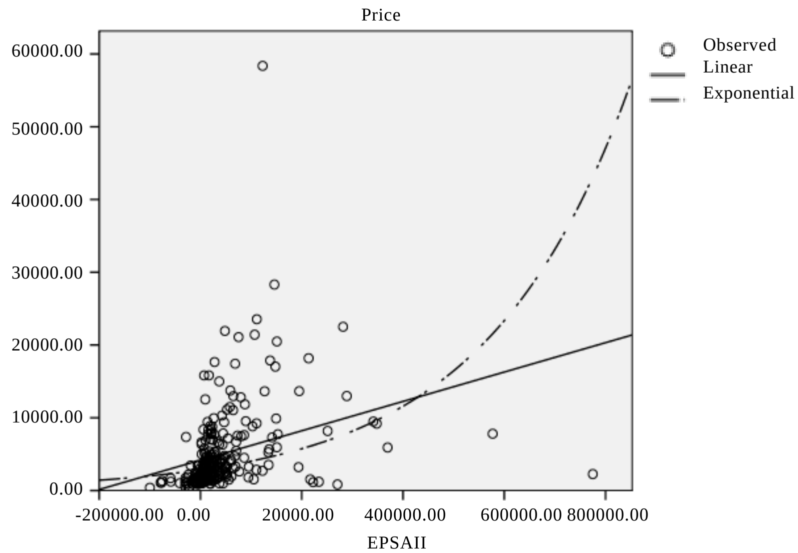

Fig. 3: Data distribution of linear and exponential regressions of the companies in the Tehran Stock Exchange

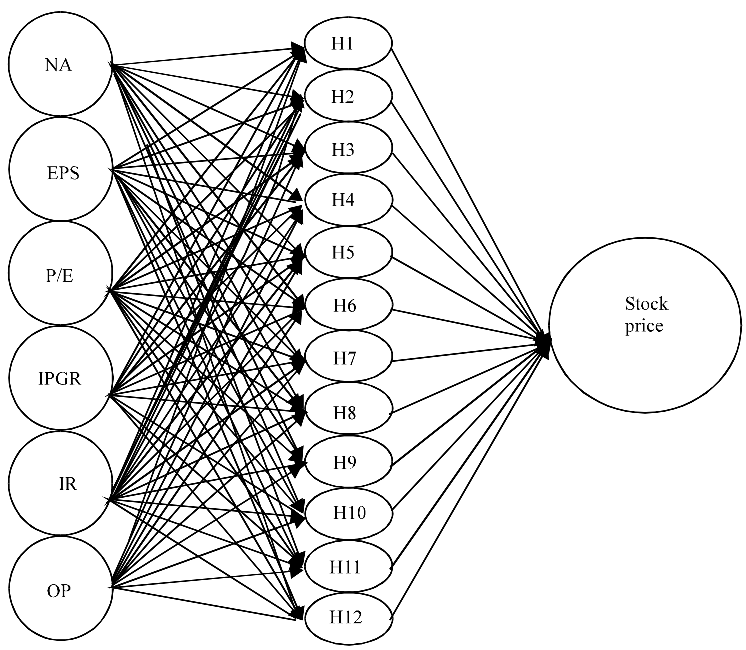

Fig. 4: Structure of ANNs with six input layer, twelve hidden layer and one out put layer. NA: Net assets, EPS: Earnings per share, P/E: Price to earnings per share, IPGR: Industrial production growth rate, IR: Inflation rate and OP: Oil prices

Input layer: In the input layer six variables or six neurons are used which include oil price, inflation, industrial production growth rate, the net assets of the company, the ratio of price to earnings per share and dividends per share. Transfer function in the first layer is hyperbolic tangent sigmoid.

Middle layer or hidden layer: In the three-layer Perceptron neural network the base processing is done by neurons in the hidden layer. In this network a hyperbolic tangent sigmoid function is used as a function of excitation for neurons in the hidden layer. There is not any general algorithm for it yet except in some special cases and selecting the number of hidden neurons often relys on past experience, or trial and error methods. So, 12 neurons are used in the middle layer that have used hyperbolic tangent sigmoid as transfer function. Repeated tests have reached this number of neurons in the middle layer. Also, the communications were comprehensive and appropriate before and after the error back propagation algorithm is prominent. Levenbery-Marquardt method of learning has been used with this large volume of data which is the fastest method of learning.

Output layer: In the network model there is a neuron in the output layer which is stock price. In the three-layer perceptron neural network, linear transfer function (stimulation) is uded. In other words, input layer and output layer can be said to make the boundary of three-layer perceptron neural network with the outside world. As such, the equation and structure of ANNs can be summarized in the Table 7.

Network mathematical equation in the MATLAB page is as follows:

```
Net                    = newff (minmax (Ldata), [6,12,1], {'tansig', 'tansig', 'purelin'}, 'trainlm')
Net.trainParam.epoch   = 300
Net.trainParam.goal    = 1e-3
Ldata                  = Data (1: rd / 2, [1 2 3 4 5 6])
Ltarget                = data (1: rd/2, [7])                                               (17)
```

In the ANNs model:

- LM learning algorithm was chosen which has the most adaptability to all survey aspects
- Value of SPREAD = 0.8326 was used because spread value of more than one will result in hype fitting in network and a larger region of input to output vector and its very small value will result in overestimation of error
- A three-layer is used in the ANNs which had six neurons in the internal layer, 12 neurons in the middle layer and one neuron in the external layer to design

Figure 5 the process of network prediction to achieve minimum error in forecasting stock price. According to network process in Fig. 5, the minimum error expressed by network with presented data was released in epochs 550 and in the middle layer with 12 neurons and with the target value of 1e-3 is equal to error of 42.3451. This error value is very reasonable with the obtained convergence value shown in the next section.

In Fig. 6 (1) First one is the amount of training error with Sum Squre Error in epochs 200, (2) Scond is the amount of Squared Weight in reaching to solidarity and (3) Third figure is effective number of parameters in training of network. Indeed, these figures depict the steps of analysis of network to be included in the final chart. That chart includes convergence or solidarity figures as shown in the Fig. 7 and 8.

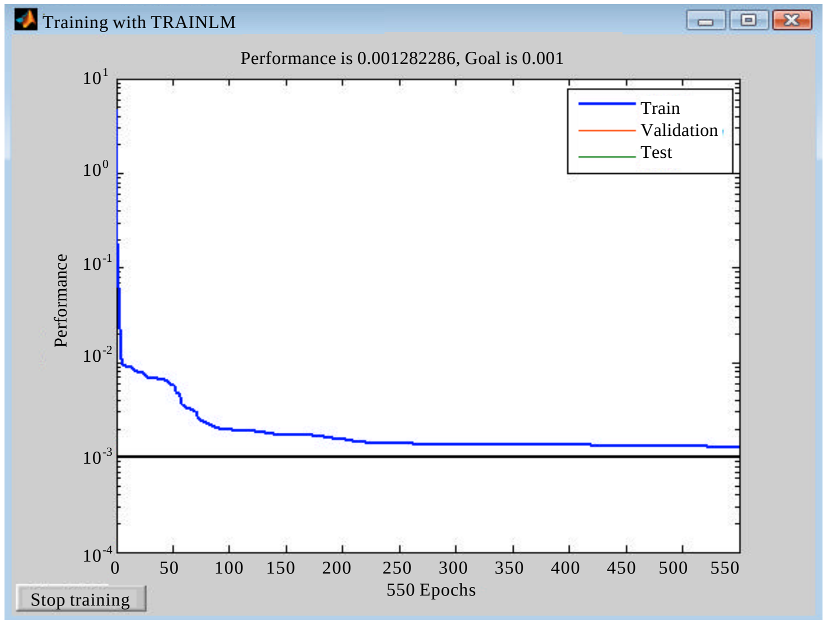

Fig. 5: Process of network prediction to achieve minimum error in forecasting stock price

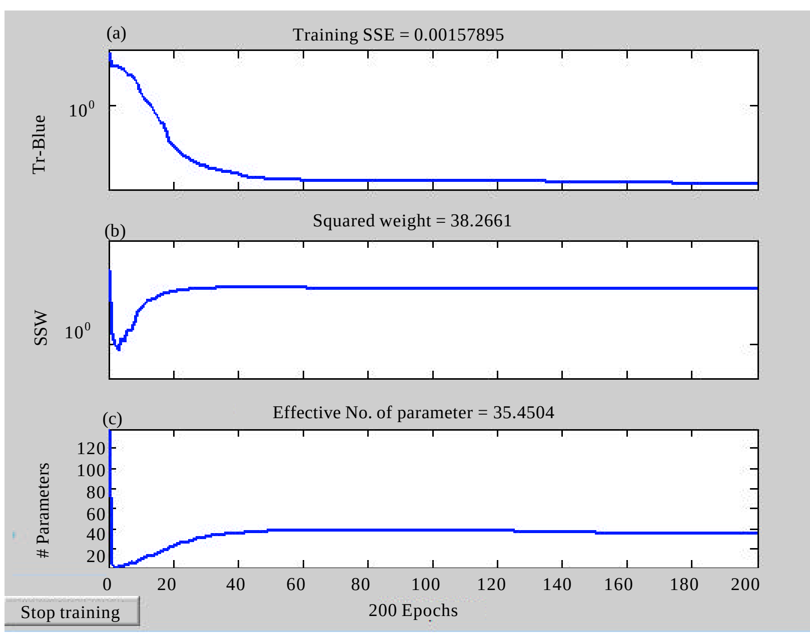

Fig. 6(a-c): (a) Amount of sum squre error of TSE listed compaines in network training step, (b) Amount of squared weight of TSE listed compaines and (c) Effective No. of parameters in 200 epoch to reach its goal

Figure 7 shows the convergence or solidarity of network. With 250 companies for four years, the correlation coefficient of 1000 data is equal to 86.041 percent and the coefficient of determination is 73.96%.

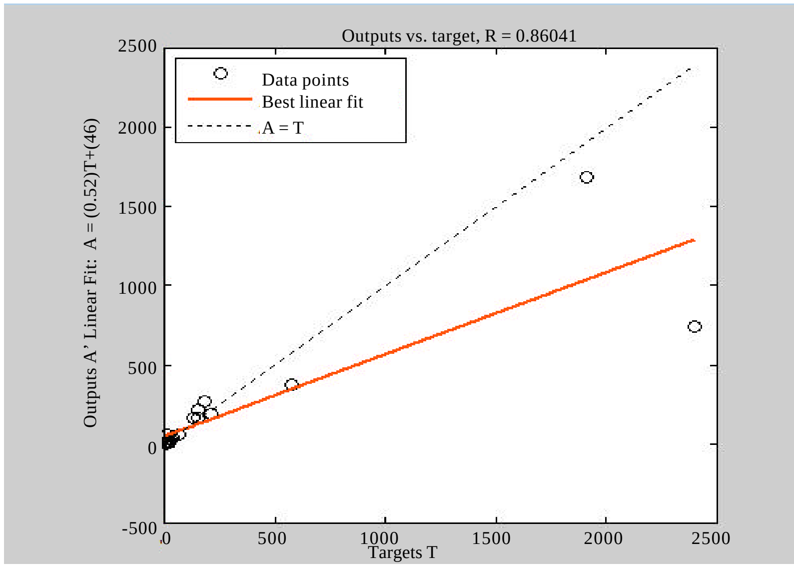

Fig. 7: Convergence or solidarity of network for all of the companies in the Tehran Stock Exchange

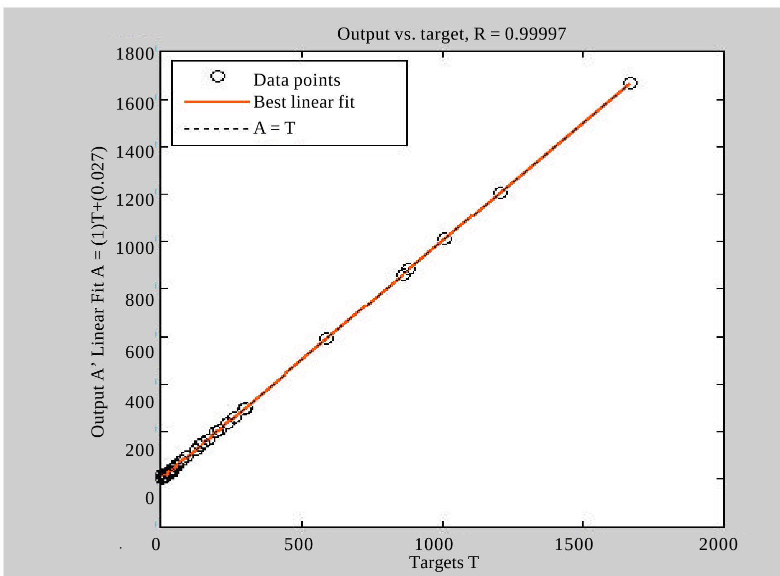

Fig. 8: Convergence or solidarity of network for one industry of the companies in the Tehran Stock Exchange

To show the strength of the model, the researchers examined their model for one industry with 66 data and the results showed that the correlation coefficients of 66 data is equal to 99.997% which was really promising (Fig. 8).

With regard to this comparison it can be found that (1) ANN's structure in this study is a powerful model and (2) If a study has just focused on one or two industry, the model cannot be a reliable model for prediction of stock prices of all stock markets.

Comparison of the analyses and determination of the best method: In this section, R (correlation coefficient) and R^2 (coefficient of determination) indexes are used. The model which has

Table 7: Architecture of multi-layer perceptron neural network of Tehran stock exchange with the No. of neurons in each layer and types of network algorithms

Network type	No. of layers	No.of input neurons	No. of middle neurons	No. of output neurons	Type of algorithm error	Type of network communication	Type of learning algorithm
MLP	3 layers	6 neurons	12 neurons	1 neuron	BP	FF	LM

MLP: Multi-layer perceptron, BP: Back propagation, FF: Feed-forward, LM: Levenbery-marquardt

Table 8: Comparison of forecasting stock prices of Tehran Stock Exchange using linear and exponential regressions and ANN methods

Model criterion	Linear regression (%)	Exponential regression (%)	Artificial neural network (%)
R	30.5	35.1	86.041
R^2	9.3	12.3	73.96

R: Correlation coefficient, R^2: Coefficient of determination

a higher solidarity and correlation coefficient indicates a more effective relationship between the independent variables on predicting the dependent variable.

In regard to the results presented in the above Table 8 it can be concluded that the ANNs are the most effective way to predict the stock price. Also, between the exponential and linear regression methods, the exponential regression method is better than linear regression.

DISCUSSION AND CONCLUSION

In the past foreign investors did not pay much attention to the TSE. Nor was the analysis of its data important to them as the TSE was not comparable to other stock markets in terms of profitability. But the dynamics of the global financial market has changed. The recent global economic recession has hit the global markets hard and has caused a steep decrease in the value of most major stocks. The confluence of these major events has shifted investors' attention toward the TSE, since the newest report from World Federation of Exchanges (WFE) reveals that the index and present value of Tehran Stock Exchange (TSE) is the second best among all the stock exchanges in the world. The present value of the TSE during the first two months of 2011 had a growth rate of 58 which placed it among the best stock markets in the world. As such it can be crucial for investors to have a rather solid estimation of future stock prices in this stock exchange. In this spirit, this research was designed to ensure investors and provide them with suitable information to make more judicious investment decision.

A number of previous studies (Cao *et al.*, 2005; Fasanghari and Montazer, 2010; Raei and Fallah-Pour, 2006; Olson and Mossman, 2003; Refenes *et al.*, 1994; Yahyazadehfar *et al.*, 2012) have attempted to reach this goal but they were limited in scope, as they have used only a limited number of industries in the TSE. To the best of previous knowledge, this is the first time in Iran that a study has used nearly all the companies in the TSE for the purpose of stock price prediction. All these companies are active, or at least active in some limited terms, that have been listed in the TSE until 2011. In order to predict stock prices by using ANNs and linear and exponential regression several models have been designed. Therefore, the results of this study can be more realistic and generalizable. Some researchers in Iran have done same study (Ebrahimpour *et al.*, 2011), their best results for trend forecasting in the TSE was 86.35% which is the same as the current prediction result which is 86.041%. On the other hand, this prediction is related to stock prices which can be of higher interest to stockholders and investors.

In this study, the researchers have tried to make an appropriate architecture for forecasting the stock price of all companies in the TSE. Going through the literature on this topic, one can reach to the conclusion that few studies conducted in Iran had these three features (1) Stock price prediction, (2) Considering all companies in the TSE and (3) Having promising results. An investor by using the model of this study can predict stock prices of all companies which have been listed in the TSE. ANNs have the ability to receive a large volume of inputs and outputs and establish a reasonable relationship between them. Thus, models based on neural networks can appropriately simulate the behavior of stock prices and offer a model which is closer to reality than classic methods. Non-linear methods can decrease the prediction errors more than the linear model because stock price behavior in market is non-linear (Tan *et al.*, 2005). This study shows the superiority and priority of the non-linear models to linear models. Other studies also found similar results (Aragones *et al.*, 2007; Cao *et al.*, 2005; Enke and Thawornwong, 2005; Refenes *et al.*, 1994; Trinkle, 2005; Yoon and Swales, 1991). The results of this study indicate that investors can use scientific methods to predict stock prices and so their investment can be successful in the stock market. According to the results of this research, stock prices can be predicted with minimal error using ANNs. The minimal error indicates the error in the test step of network and then in the training step of original data. So, investors by using the inputs listed in the pages before which can be easily obtained and being familiar with MATLAB software can predict the stock price of the companies present in the TSE. It must be considered that the findings of this study are realistic. Maybe the results of prior studies in the prediction of stock price had less error but they just studied specific industries and their findings cannot be extended to other industries. Instead, in this study a specific company or even a particular industry is not addressed; therefore, the findings of this study can be used for all industries or companies in the TSE. It is noteworthy that this research is more important in comparison with many other studies in Iran, because the present study is a comprehensive and general model to predict stock prices. This is one of the most superior factors of this study in contrast with previous studies.

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