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Combination Neural Network and Financial Indices for Stock Price Prediction

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Abstract: As the stock market data is non-stationary and volatile the investors feel insecure during investing. In the recent years lots of attention has been devoted to the analysis and prediction of future values and trends of the financial market. In recent years, mathematical methodology has been used by financial experts and brokers. This study presented Neural Network (NN) approach to develop an efficient model for stock price prediction. Financial ratios were included Earnings Per Share (EPS), Prediction Earnings Per Share (PEPS), Dividend Per Share (DPS), price-earnings ratio (P/E) and earnings-price ratio (E/P) which were extracted from Tehran stock exchange during a decennial period (2000-2009). The training and testing sets were used to develop the NN model. The developed models were subjected to a sensitivity analysis test to assess the relative importance of input variable on model output. Quantitative examination of the goodness of fit for the predictive models was made using R^2 and error measurement indices commonly used to evaluate forecasting models. Statistical performance of the developed NN model revealed close agreement between observed and predicted values of stock price, indicates that MLP type NN appears as a promising method for modeling the relationship between financial indices and stock price. The sensitivity analysis indicated that the stock price was more sensitive to DPS followed by EPD, PEPS, E/P and P/E, respectively. In conclusion, the developed NN model could satisfactorily predicted the stock price based on financial indices. Moreover, these models can serve as useful option in determining the relative importance of input variables on model output.

Key words: Multiple perceptron, artificial neural networks, stock price index, financial ratios, stock price prediction

INTRODUCTION

Stock price prediction is one of the main tasks in all private and institution investors. Stock price prediction is not a simple task (Tehrani and Khodayar, 2010). It is an important issue in investment/ financial decision-making and is currently receiving much attention from the research society. However, it is regarded as one of the most challenging problems due to the fact that natures of stock prices/indices are noisy and non-static (Hall, 1994; Li *et al*., 2003; Abu-Mostafa and Atiya, 1996).

The price changing of stock market is a very dynamic system that has drive from a number of disciplines. Two main analytical approaches are fundamental analysis and technical analysis. Fundamental analysis uses the macroeconomics factors data such as interest rates, money supply, inflationary rates and foreign exchange rates as well as the basic financial status of the company. After scrutiny all these factors, the analyst will then make a decision of selling or buying a stock. A technical analysis is based on the historical financial time-series data. However, financial time series show quite complex data (for example, trends, abrupt changes and volatility clustering) and such series are often non-stationary, whereby a variable has no clear tendency to move to a fixed value or a linear trend (Chang and Liu, 2008). The idea of setting up in Iran a well-established stock exchange goes back to the 1930s. In 1968, Tehran Stock Exchange (TSE) established and started trading shares of a limited number of banks, industrial companies and State-backed securities. The TSE is a small exchange center in terms of the size, turnover and other financial indicators. However, only common shares and participation securities are trading there. Moreover, there are no derivatives, nearly impossible to hedge and therefore, the risks are very high. In TSE there is a great lack of knowledge and expertise among the TSE's staff as well as the brokers and investors (Parchehbar and Talaneh, 2010).

The aim of this paper was the application of MLP for prediction of stock price in cement industry. Within this work, financial indices and closing prices in decennial range (2000-2009) have been used that have taken from TSE. The new approach in this paper was using MLP and

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integrated it with financial indices in prediction of stock price for helping investor and financial analyst.

Prediction of stock price variation is a very difficult task and the price dynamism behaves more like a random walk and time varying. Initial research work essentially on this topic was based on statistical approach such as regression, correlation and spectral analysis (Majhi *et al*., 2008). Al-Zu'bi *et al*. (2010) developed a fuzzy model for forecasting the Nile river flow. The correlation and spectral based models were successful but led to poor prediction quality due to nonlinear assumption of financial time series such as strong autocorrelation, stationary characteristics and linear structure (Bodyanskiy and Popov, 2005; Majhi *et al*., 2008). Lately, artificial neural networks (ANNS) have been applied to this task. (Atsalakis and Valavanis, 2009; Cao and Parry, 2009; Chang *et al*., 2009; Chavarnakul and Enke, 2008; Enke and Thawornwong, 2005; Hassan *et al*., 2007; Hasangholipour and Khodayar, 2010; Kim, 2006; Tsang *et al*., 2007; Vellido *et al*., 1999; Zhang and Wu, 2009; Zhang *et al*., 1998; Zhu *et al*., 2008). These approaches have their limitations owing to the prodigious noise and complicated dimensionality of stock price data and besides, the quantity of data and the input variables may also intervene with each other. Therefore, the result may not be that unpredictable (Chang and Liu, 2008).

Kuo *et al*. (2001) used a genetic algorithm base fuzzy NN to determine the qualitative effects on the stock price. Aiken and Bsat (1999) applied a feed forward NN trained by a Genetic Algorithm (GA) to forecast three-month US Treasury Bill rates. They conclude that an NN can be used to truly predict these rates. Thammano (1999) used a neuro-fuzzy approach to predict future values of Thailand's largest governmental bank. Conclusion of this research was that the neuro-fuzzy architecture was able to identify the general traits of the stock market easier and more accurately than the basic back propagation algorithm. Also, it would obtain prediction possibility of investment opportunities during the economic crisis when statistical methods did not yield trusty results (Chang and Liu, 2008). Tansel *et al*. (1999) compared the ability of linear optimization, ANN and GA in modeling time series data and concluded that the best estimate is related to linear optimization methods, followed by GA, if the boundaries of the parameters and the resolution were suitable and NN. Baba *et al*. (2000) used NN and GA to create an intelligent Decision Support System (DSS) for analyzing the Tokyo Stock Exchange Prices Indexes (TOPIX). They suggested the buy and sell decisions based on the average projected value. Kim and Han (2000) combined a modified NN and a GA to predict the stock price index. The GA was used to reduce the complexity of the feature space, by optimizing the thresholds for feature discretization and to optimize the connection weights between layers. Amiri *et al*. (2009a) designed a new model of effective financial factors on TEPIX (stock price index in Tehran stock exchange) with structural equation model and fuzzy approach.

Abraham *et al*. (2001) investigated hybridized SC approaches for prediction of automated stock market and trend analysis. Abraham *et al*. (2003) investigated how the seemingly erratic behavior of stock markets could be well formulated using several connectionist paradigms and soft computing techniques. The result of their study was that all the connectionist paradigms considered could represent the stock indices behavior very accurately (Chang and Liu, 2008). Hwang (2006) used a fuzzy GMDH-type NN model for prediction of mobile communication. Amiri *et al*. (2009b) used a fuzzy approach for investigation and explanation of local model of internal effective factors on stock price index in Tehran Stock Exchange. They showed the proposed neuro-fuzzy GMDH method was excellent for the complicated forecasting problems. Srinivasan (2008) developed GMDH type NN for prediction of energy demand. This paper presented a medium-term energy demand forecasting method that helps utilities identify and forecast energy demand for each of the end-use consumption sector of the energy system, representing residential, industrial, commercial and public lighting load.

Also, we have to refer other forecasting model in different areas for example in temperature forecasting by NN (Hayati and Mohebi, 2007), daily flow forecasting by NN and K-nearest neighbor methods (Eskandarinia *et al*., 2010), suitability of NN in daily flow forecasting (Solaimani and Davari, 2008) and long term load forecasting in power systems based on grey systems prediction-based models (Askari and Fetanat, 2011).

In this research input data include indices of EPS, PEPS, DPS, P/E and E/P. The main reason for selection these indices are using for prediction process by financial experts and stock holders. In Tehran Exchange market, supply and demand determine stock prices and the supply and demand in the Exchange is done by brokers. Therefore, information should be clear that the brokers use of it in decisions related to buying and selling. Referring to the stock brokers and consult with them realized that investors for decisions related to buying and selling shares are use information such as: Earnings Per Share (EPS), Prediction Earnings Per share (PEPS), Dividend Per Share (DPS), price-earnings ratio (P/E) and earnings-price ratio (E/P).

Stock price is defined as output data. All indices are defined below: Earnings Per Share (EPS) is one of the most important measure of companies strength. The significance of EPS is obvious, as the viability of any business depends on the income it can generate. A money losing business will eventually go bankrupt, so the only way for long term survival is to make money. EPS allows us to compare different companies' power to make money. The higher the EPS with all else equal, the higher each share should be worth. To calculate this ratio, divide the company's net income by the number of shares outstanding during the same period (Ghalibaf Asl, 2010).

- Prediction Earnings Per Share (PEPS) is the last of prediction earnings per share. On the other hand, it is unrealized EPS (Ghalibaf Asl, 2010)
- Dividend per share (DPS) is the total dividends paid out over an entire year (including interim dividends but not including special dividends) divided by the number of outstanding ordinary shares issued (Ghalibaf Asl, 2010)
- Price-earnings ratio (P/E) value investors have long considered the price earnings ratio one of the single most important numbers available when evaluating a company's stock price. The P/E looks at the relationship between the stock price and the company's earnings and it is the most popular metric of stock analysis. The price earnings ratio is equal to the price of the stock divided by EPS of common stock (Ghalibaf Asl, 2010; Jahankhani and Parsaieyan, 2010)
- Earnings-price ratio (E/P) is a way to help determine a security's stock valuation, that is, the fair value of a stock in a perfect market. It is also a measure of expected, but not realized, growth. It may be used in place of the price-earnings ratio if, say, there are no earnings (as one cannot divide by zero). It is also called the earnings yield or the earnings capitalization ratio. E/P is equal to the EPS of common stock divided by the price of the stock (Ghalibaf Asl, 2010; Jahankhani and Parsaieyan, 2010)
- Stock price is equal to the last of Stock price which trading at the one day (Ghalibaf Asl, 2010; Jahankhani and Parsaieyan, 2010)

RESEARCH METHODOLOGY

MLP methodology: Artificial Neural Networks (AANs) are increasingly used in problem domains involving classification (Yedjour *et al.*, 2011). The idea of neural networks was first inspired by human beings nervous system which consists of a number of simple processing units called neuron (Fig. 1). Each neuron receives some signals from outside or from other neurons and then by processing them in activation function produces its

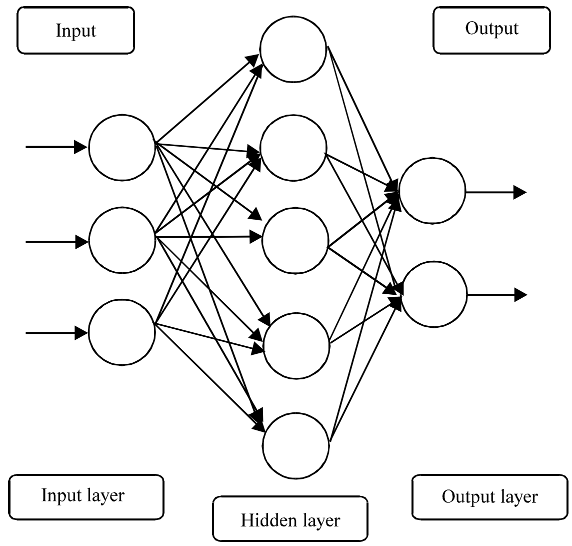

Fig. 1: Structure of a feed forward MLP

output and sends it to other neurons. Each input impact is different from other inputs. For example in figure two the impact of the ith neuron on jth neuron is shown with w_{ij}, the weight of the connection between neuron i and j. Consequently the more is the weight w_{ij} the stronger would the connection be and vice versa. In this study, main focus was on feed forward multi layer NNs. These networks are made of layers of neurons. The first layer is the layer connected to the input data. After that there could be one or more middle layers called hidden layers. The last layer is the output layer which shows the results. In feedback networks in contrast with recurrent networks all the connections are toward the output layer. Figure 1 shows a three layer feed forward Perceptron network (Fig. 2).

A multilayer perceptron (MLP) neural network is an extremely popular and widely documented architecture (Tahir *et al.*, 2006). One of the learning methods in MLP type NN is the back propagation error in which the network learns the pattern in data set and justifies the weight of the connections in the inverse direction in order to regularize the sum of squared error. The back propagation method picks a training vector from training data set and moves it from the input layer toward the output layer. In the output laye, r the error is calculated and propagated backward so the weight of the connections will be corrected. This will usually go on until the error reaches a pre defined value. It's proved that one can approximate any continuous function with a three layer feedback network with any precision. It should be said that the learning speed will dramatically decrease according to the increase of the number of neurons and layers of the networks.

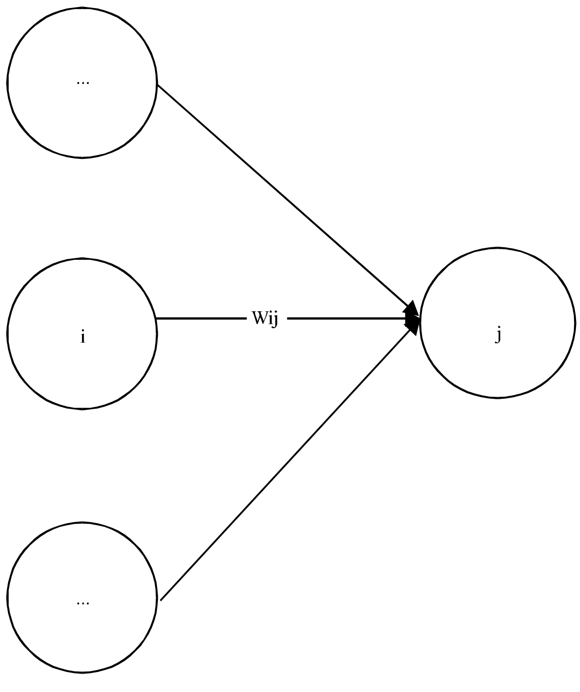

Fig. 2: Perceptron neuron's connections

The MLP network sometimes called Back Propagation (BP) network is probably the most popular ANN in engineering problems in the case of non-linear mapping. It consists of an input layer, a hidden layer and an output layer. The input nodes receive the data and pass them to the first hidden layer nodes. Each one collects the input from all input nodes after multiplying each input value by a weight, attaches a bias to this sum and passes on the results through a non-linear transformation like the sigmoid transfer function. This forms the input either for the second hidden layer or the output layer that operates identically to the hidden layer. The resulting transformed output from each output node is the network output. The network needs to be trained using a training algorithm such as back propagation, cascade correlation and conjugate gradient. Basically, the objective of training patterns is to reduce the error. The goal of every training algorithm is to reduce the error by adjusting the weights and biases.

The stock price prediction using MLP: The quality of developed NN based models mostly depends on a proper setting of neural network architecture which is learning algorithm, transfer functions, range and distribution of data used for training and testing set. In our study feed forward multilayer perceptron employed to predict the stock price. The variables of interest for constructing this model consisted of EPS, PEPS, DPS, P/E and E/P. The configuration of developed models consisted of only one hidden layer, the hyperbolic tangent considered as an activation function, whereas Quasi-Newton was used as a training algorithm. Two different random data groups were considered in developing models. The first group was the training set and used for updating the network weights and biases. The remainders considered as the testing set which was used for examine the final quality of developed models. The Statistica Neural Networks software version 8.0 was used to construct and train the NN models (StatSoft, 2009). Quantitative examination of the predictive ability of both models was made by R2, MS error and bias.

Sensitivity analysis: The sensitivity analysis technique indicates the input variables which are considered as the most important variables in developed model. This method often identifies variables that can be safely ignored in subsequent analysis and key variables that must always be retained. There are several approaches for conducting sensitivity analysis. The sensitivity of stock price predictive model to DPS, E/P, P/E, PEPS and EPS, as input variables, determined by missing value problem proposed by Hunter *et al.* (2000). In this method, each input variable is replaced in turn with missing values and the effect upon the output error, named Variable Sensitivity Error (VSE) is assessed. By the same token, the Variable Sensitivity Ratio (VSR) value is a relative indication of the ratio between the VSE and the error of the developed model when all variables are available. The more important variable is matched with the higher VSR.

RESULTS AND DISCUSSION

Figure 3 and 4 shows the relationships between the actual and the estimated values for stock price prediction model for training and testing set, respectively. If the acquired model is completely precise, all data points will lie on the straight line through the origin. Most of the data formed a cluster along the solid line. This means that the NN-based model was constructed successfully with high accuracy (Fig. 3, 4). The statistical results for the prediction ability of NN models are shown in Table 1. Based on the criteria selected to evaluating the performance of NN models (R^2, MSE and Bias), the performance of predictive models were satisfying. Gaining high values for R^2 in both training and testing set indicated that over-learning and under-learning didn't occurred in developed models. Ability of a NN model to estimate output variable accurately when presented with input variables never seen during training (i.e., testing set) is called generalization ability. Over-learning is observed when the NN model memorizes the training data but

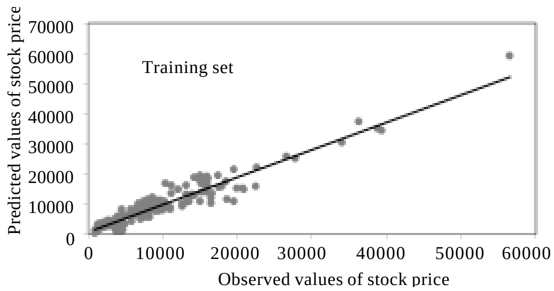

Fig. 3: Scatter plot for comparison between the predicted and observed values of stock price in developed neural network models in training set. The solid line indicates the fitted simple regression line on scatter points

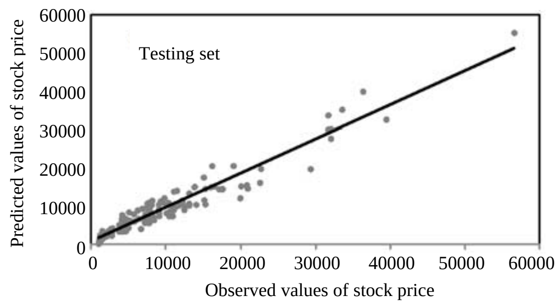

Fig. 4: Scatter plot for comparison between the predicted and observed values of stock price in developed neural network models in testing set. The solid line indicates the fitted simple regression line on scatter points

Table 1: Model statistics and information for stock price prediction

	Data sets	
Statistics	Neural training	Neural testing
R^2	0.91	0.93
RMSE	2399.6	2377.8
Bias	29.3	114
Information		
Type of network	Three layer perception	
Training algorithm	Quasi-Newtonian	
Hidden layer	1	
Hidden neurons	6	
No. of data lines	176	147

RMSE = Root mean square

cannot generalize well. Under-learning is a situation where the NN model has difficulties even to learn the training data itself. Possible reasons for such situations are insufficient hidden neurons, or insufficient training, or training gets stuck in a local minimum (Devabhaktuni *et al*., 2001). The distribution of the residual values, difference of observed and predicted values of stock price, about zero mean obtained by NN models for training and testing sets are shown in Figure 5 and 6, respectively. In our study, the calculated

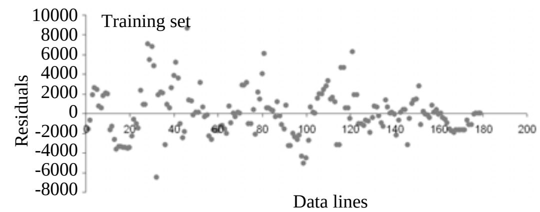

Fig. 5: Neural network models residuals versus corresponding data lines in training set. The residuals indicate the differences between actual and predicted values of stock price using neural network models

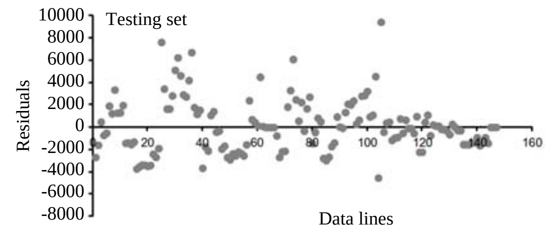

Fig. 6: Neural network models residuals versus corresponding data lines in testing set. The residuals indicate the differences between actual and predicted values of stock price using neural network models

Table 2: Overall sensitivity analysis of input variables in the neural network models for stock price prediction

	Input variables				
Model	DPS	EPS	PEPS	E/P	P/E
Stock price					
VSR	10.6	7.63	5.6	2.3	1.9
Rank	1	2	3	4	5

VSR: Variable sensitivity ratio. EPS: Earnings per share; PEPS: Prediction earnings per share; DPS: Dividend per share; P/E: Price-earnings ratio; E/P: Earnings-price ratio

values of VSE and VSR were considered as criteria to determine the relative importance of input variables (EPS, PEPS, DPS, P/E and E/P) on models output (stock price). The overall sensitivity analysis of input variables in the neural network model for stock price prediction summarized in Table 2. The input variables with VSR = 1, may safely be ignored in the model development. Whereas the higher value of VSR indicates the more important variable in developed model. In the developed NN model in this study, the calculated values of VSR for input variable were bigger than 1 (VSR = 1), which indicates that our selected input variables significantly affect the stock price. The same findings reported by researchers aimed to investigate the effect of EPS, PEPS, DPS, P/E and E/P on stock price. The sensitivity analysis results of the constructed NN models indicated that the stock price value were more sensitive to DPS followed by EPD, PEPS, E/P and P/E, respectively.

CONCLUSION

The present study showed that the MLP type NN can be used to predict stock price based on financial indices. For a long time, there has been much interest in predicting the stock price index. However, in recent years, stock price prediction is one of the most challenging problems due to the fact that stock prices/indices are inherently noisy and non-stationary. Statistical performance of the developed MLP model revealed close agreement between observed and predicted values of stock price. The advantage of using NN model is subjecting the developed model to analysis of the sensitivity of output with respect to input variables. The sensitivity analysis results of the constructed NN models indicated that the stock price value were more sensitive to DPS followed by EPD, PEPS, E/P and P/E, respectively. Sensitivity analysis has several effects such as obtaining the first-order approximation solution, evaluating the parameters' sensitivity, selecting proper variables and applying the results to give practical solutions.

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