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Investigating the Accuracy of Artificial Neural Network for Forecasting Share Price of Various Industries in Tehran's Stock Exchange

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ABSTRACT

Accuracy in forecasting the price of share in the stock exchange is important for shareholders and investors because it helps them to decide whether to investment or not and a correct decision will give them the highest return on their investment. The purpose of this research is to study the relationship between the type of industry and the accuracy of forecasting the price of shares using an artificial neural network. A multi-layer Perceptron neural network was designed with an error backward propagation algorithm and sigmoid transfer function for 183 firms in 12 industries and 7 fiscal years with input including the monthly average price of an ounce of Gold, the monthly average price of oil (based on OPEC), the monthly average rate of inflation (base year 2004), the monthly average price of reference foreign exchange ($ U.S.A), and the monthly average interest rate on a (short term account); and the output was the price of shares of various firms. The results confirmed the hypothesis.
KEYWORDS: price of shares, artificial neural network, error backward propagation algorithm, industries on Tehran`s stock exchange.

1. INTRODUCTION

Investors usually invest in the stock exchange with two aims: temporary investment of surplus cash moneys and long term invest to increase income. Investor soften have surplus cash that it cannot be needed and they invest in a short-term account or they invest for trading to increase the possibility of profitability directly or indirectly[1]. Therefore one of the main objectives of investment in the stock exchange is to gain earnings and forecasting the price of shares so it is an important issue for investors. Investors have expended enormous efforts on trying to find a useful tool to forecast stock market trends accurately, enabling them to maximize their profits. [2].This forecasting is not a simple job in due to because of the complexity of the market; many market factors that participate in determining the price of shares cannot be considered in a technical analysis.

The continuous development of the economy has led to rapid increases in investment markets. Nowadays, investments in the stock exchange form an important part of economy of a society's economy. This is why the forecasting of the price of shares is important, so that investors can gain the highest return [3]. Forecasting has been considered as the most important scientific branch in economics, trade, and accounting subjects and develops daily. Managers of different economical, trade and accounting prefer to have a mechanism with effective variables which can help them in decision making. They want to have a method for making a true [4]. Classic methods have been used in forecasting the price of shares in previous years but by continual development, methods using artificial neural networks have become widely used. Artificial neural network (ANN) technique is one of data mining techniques that is gaining increasing acceptance in the business area due to its ability to learn and detect relationship among nonlinear variables. Also, it allows deeper analysis of large set of data especially those that have the tendency to fluctuate within a short of period of time. This makes ANN a candidate for stock market prediction, much research efforts computational efficiency of share values [5].

2. Background

Azaret al. (2006) compared classic methods and artificial intelligence for forecasting the index of share prices and designing a combinatory method. They have evaluated the operation of classic methods such as exponential methods, process analysis, ARIMA, and artificial intelligence, including neural networks and phase neural networks. Then a third scenario, namely designing a combinatory method from ARIMA, neural networks, and phase neural networks was studied. In this research, input variables included the price of foreign exchange, price of oil, ratio of P/E, volume of exchanges, economic inflation and indexes (CPI, PPI…). Different types of functions such as

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sigmoid, hozloli tangent, logarithmic sigmoid, and linear and intensive limitative functions were used for selecting the middle layer function. The learning algorithm used in this research was an error backward propagation algorithm and the number of training repetitions was 3000 times. The results showed that the extent of artificial intelligence method error was less than the error for all of classical methods. However, the extent of error for the combinatory method error was less than for the classical and artificial intelligence methods.

Azar and Afsar (2006) compared forecasting of price of shares modeling by procedure of phase neural networks in terms of operation scale with ARIMA method for 5 years. Twenty-five percent of the data were selected as experimental data and the other data were used for validation. An error backward propagation learning algorithm and a Sagno phase deduction system with input function and sigmoid and nonlinear function used for the not-being phase by movable average function. One hundred membership functions were used in this research. The results showed that phase neural networks has been surpassed the ARIMA method in whole six scales of operation evaluation and have the unique specifications of rapid convergence and high accuracy; in addition they are suitable for forecasting an index of share prices.

HeidariZare and Kordloei (2009) investigated the forecasting of share prices by using an artificial neural network in the Ghadir Investment Firm for 4 years. The independent input variables included the total price index for the stock exchange in Tehran, the price of the dollar in the free market, and the prices of oil and gold. Eighty percent of the data were used for training, 10% were confirmatory, and 10% were experimental. The design of the network was in form of 5-30-1and different functions were tested in different layers. The best transfer functions were the logistic function for the output layer and the hyperbolic tangent function for the other layers. The optimized scale of training repetitionswas according to the stop method on time, which is in 8900repetitions. The results showed that when the data were divided randomly, MLP gave a more suitable forecast and that after adding new data to this network and training it again, the answer will be better than the previous one. Therefore it is possible for neural networks to maneuver on change of network and hereby, change the results, but the results of forecasting can be improved by changing the number of variables in the regression and in many other forecasting models.

TolooeiAshlaghi and Haghdoost (2004) tested share price forecasting by comparing a neural network with mathematical forecasting methods. The model they used was a popular advance spending network with three hidden layers that had six elements in the first hidden layer, four elements in the second layer, and four elements in third layer, and a nonlinear sigmoid function with 20,000 training repetitions. The network was trained randomly and not returnable. The average quadrate error in the neural network was more than that in the regression model. This is not adapted to the related observation with the previous studies and basic default. They found that forecasting with regression provided a better solution than did the neural network model in Iran Khodro firm. Therefore, a neuralnetwork is not always a suitable solution for any situation.

Motevaseli and Talebkashefi (2006) compared the potency of artificial neural network with input from technical analytical indexes to forecast share prices. In this method, the prices of shares of 40 firms in the stock exchange were forecasted, by using three different methods, for the future 10 days. In the first method, the price was forecasted using a one-layer advance spending neural network with Lonberg-Marguat training algorithm and operation scale of mean square errors with the input of market value. Then, in addition to the market value input, moveable averages of 5 days, 10 days, and 20 days and an ROC, RSI of 12 days were introduced as input to the network and forecasted. The price of shares was forecasted using the ARIMA model for all firms. Three different methods of forecasting were compared using variance analysis. As the forecasting of prices for 30 firms by the ARIMA model had better results than by the neural network models, it can said that linear models can analyze the complexity of time series of share price better than nonlinear models.

Sinaei et al. (2005) tested forecasting of Tehran's stock exchange index using an artificial neural network. Two sets of data were selected for input to the neural network. Different intervals of indexes and macro-economic factors were the independent variables for the neural networks used in this research as kind of multi-layer Perceptron and trained by an error backward propagation algorithm that included three-layer and four-layer advance spending neural networks with a different number of neurons in the input and hidden layers. A linear ARIMA model was used to forecastthe index of prices for the following week. The results show that neural networks operate better than the linear ARIMA model, and an acceptable amount of MSE for of the network test data shows that riotous behavior in the price index. A test of r^2 shows some evidence against the market hypothesis and random veer. among the various interval data of index, the best network modeled for forecasting of share prices is the three-layered neural network 3-15-1, with three intervals input of index and 299 training repetitions with MSE= 5710 and R2= 0.999.

Raei and Chavoshi (2003) studied the forecasted return on shares in the Tehran stock exchange using an artificial neural network and a multifactor model. To test this situation, the daily price of shares of the BehshahrFirm was selected as a sample. The independent research variables (inputs) were macro-economic variables, for example the total index of prices in the Tehran stock exchange, the price of the dollar in the free market, and the prices of oil and gold. Multivariable linear regression was used to test the factor model and MLP architecture with a training error backward propagation algorithm was used to test the artificial neural network. The results showed success for two models in forecasting share returns and the superiority of the artificial neural network operation over the multifactor model.

Azar and Rajabzadeh (2003)evaluated methods of combinatory forecasting using a classic- neural networks method in the field of economics. Forecasting was done by different methods, called individual methods in this research. Individual forecasting models included exponential smoothing methods, process analysis, box-Jenkins, causal analysis, and a neural network model. The results of the individual methods were compared using an artificial neural network and multivariable regression. The data were the demand of OPEC for oil from 1960 to 2002 as the dependent variable and price, income and demand of other energies, population, and added value in industry section as independent variables. The data used for all variables were from 1960 to 1996 and test data were from 1996 to 2002. The results showed that error in combinatory methods was less than that in individual methods and that suitable combinatory methods were neural networks methods and multivariable regression, in that order.

Moshiri and Morovat (2006) explored forecasting the total index of returns in the Tehran stock exchange using linear and nonlinear models. The total index of returns in the Tehran stock exchange was forecasted by using daily and weekly data from 1998 to 2003 and forecasting methods of ARIMA, ARFIMA, GARCH and the neural network ANN. A comparison of the forecasting accuracy of these models by forecasting scales of RMSE, MAE and U-THIEL shows that the ANN model operates better in forecasting daily and weekly index than the other models, but a statistical comparison of the forecasting accuracy of the different models using the Diblid-Maryano statistic does not show meaningful difference between the forecasting accuracy of these models. According to results, it can be recommended to researchers to use ARFIMA and ANN nonlinear models to forecast share prices in Tehran.

Lawrence et al. (1993) used a neural network to select shares for 120 firms. An error backward propagation algorithm was used for training the network. Input variables included gross earnings, current ratio, net earnings, return of capital, and ratio of total debt to capital. The results showed the accuracy of the network in forecasting future share returns.

Angelos (2001) studied the linear forecasting of a neural network for return on shares from 1980 to 1994. The number of observations was 234 for every series. The input variables includedthe percent of changes in volume of exchanges and the percent of changes in earnings. An error backward propagation algorithm and a logistics transfer function were used in this research. The results showed that forecasting using an artificial neural network can explain errors of forecasting in the linear model, while the linear model cannot explain errors of forecasting in the artificial neural network. Therefore, forecasting using an artificial neural network is preferable to forecasting using linear model.

An-sing et al. (2003) neural networksto forecasting in an emerging financial market Taiwan from 1982 to 1992. Input variables were rate of short term interest, index of returns, level of consume, internal and national gross productions, price of consumption, level of production and output variable, shares index return. The results showed that investment strategies based on artificial neural networks are more efficient than other investment strategies tested in this research.

Lendasse (2000) forecasted the index using a neural network. Input data were two types of data: exogenous and endogenous. The economical exogenous data were the international index of share prices, the price of exchange transfer (dollar, mark and yen) and interest fees (three months and treasury) and the endogenous data were the historical amount of the index. The results of this research showed that neural networks perform better than linear methods.

Chiang et al.(1996) studied a neural network method for forecasting the net price of investment firms. They used a neural network with an error backward propagation algorithm. They compared the network data with their results from traditional econometrics methods and found that neural networks perform better than regression methods when the data were low. In other research, a kind of neural network was created to input quality factors such as political effects along with quantity factorswhich were. This form of network, a combination of a neural network and a Delphi mode, was the basis of quality network. They tested their model in Taiwan's stock exchange.

3. Hypothesis

There is a meaningful difference between industry type and the accuracy of share price forecasting using an artificial neural network

4. Methodology

This research is an applied-descriptive study, which uses illative tests(mean square error and mean absolute error) for confirmation or refusal of the hypothesis.

5. Statistical sample and population

The statistical population of this research was all accepted firms in Tehran's stock exchange which had been active in the stock exchange from the beginning of 2003 to 2009. These firms are placed in the stock exchange according to their activities in one of 31 industries. An eliminative method was usedto select a suitable statistical sample from this population. Two criteria were considered for this and if a firm had both criteria, it was selected as a sample firms. The criteria are as follows:

1) The firms should have continuous activity in the stock exchange from2003 to 2009.
2) The industries with less than 5 firms while taking one criteria, were eliminated from the population until a minimum of 30% of the firms in every industry were placed in sample.

See Table 1 for the number of firms in the sample.

Table 1 - State of the firms'membership in the statistical sample within various industries.

Industry	Type of Industry	Number of Accepted In the Exchange To the End of Year 2010	Number of Qualified members in the Sample
1	Mining	11	7
2	House Clumping, Properties and Pertaining	13	6
3	Various Types of Food and Drink Products	51	20
4	Automobile and Parts Construction	31	25
5	Food Stuffs and Chemical Products	66	39
6	Electrical Networks and Machinery	13	7
7	Metallic Manufacturers Construction	16	5
8	Financial Mediatory Industry	27	9
9	Rubber & Plastic	16	5
10	Machinery &Equipments	34	12
11	Basic Metals	31	13
12	Nonmetallic Mine Products	66	35
Total		375	183

6. Variable and how to account and derivation it

Using software from the informing firms, Exchange Services, and information banks in the internet, a total of 92,232 data points were derived. See Table 2.

Table 2 - Variables and how to account and derivation it

	No.	Variable	Data	Source	Account Manner
Predicting variables (independent)	1	Monthly average Price of an Ounce of Gold	Monthly average of Gold Price	Site kitco.com	Monthly Total Amount of Gold Price /Number of Prices
	2	Monthly average Price of Oil(OPEC)	Monthly average of Oil Price	Site ioga.com	Monthly Total Amount of Oil Price /Number of Prices
	3	Monthly average Rate of Inflation (Base Year 2004)	Monthly average of Inflation Rate	Central Market Site	Monthly Total Inflation Rates/ Number of Rates
	4	Monthly average Rate of Reference Currency (U.S.A Dollar)	Monthly average of Currency Rate	Central Market Site	Monthly Total Currency Rates/ Number of Rates
	5	Monthly averageRate of Interest (Short time Deposit on Account Interest Rate)	Monthly average of Interest Rate	Central Market Site	Monthly Total interest Rates/ Number of Rates
Predicted variable (dependent)	1	Shares Price	Shares Price	Valuable Papers Exchange Site	Monthly Total Amount of shares Prices/ Number of Prices

7. Data Analysis

A neural network model for each firm was designed in MATLAB software as a 5-12-1, which means 5 input layers, 12 hidden layers, and 1 output layer. The number of repetitions for network training was 1000 times. In this limit, the error rate has been reduced to about ($10^{-6.5}$) and the network has been prevented from extra training, which causeserrors to increase error.In general, 92,232 collected data points and (6 Variable *12 Months* 7 Fiscal Years) 504 data points for the designed neural network, was specialized for each firm; 70% of the samples were used for training, 15% for Testing, and 15% for evaluation.

8. Research Data

In Table 3, industries have been arranged in the order of lowest to highest average MSE. In Table 4, the order is based on the amount of average MAE. As we can see, the least error in the neural network is in the Non-metallic Mine Products Industry and after that, is the Automobile and Parts Construction Industry. And the highest error is related to the Food Stuff Industry and Chemical Products and Mining Industry.

Table 3- Mean square error classification of shares price forecasting in various industries

Name of Industry	MSE
Non-metallic Mine Products	0.0095
Automobile and Pieces Construction	0.0111
Rubber & Plastic	0.0119
Various type of Food and Drink Products	0.0129
Financial Mediatory Industry	0.0129
Basic Metals	0.0135
House Clumping, Properties and Pertaining	0.0142
Metal Products Construction	0.0145
Machinery and Equipments	0.0155
Electrical Machinery and Networks	0.0161
Food Stuffs and Chemical Products	1.0175
Mining	0.0178

Table 4- Mean absolute error classification of shares price forecasting in various industries

Name of Industry	MAE
Non-metallic Mine Products	0.0500
Automobile and Pieces Construction	0.0551
Various type of Food and Drink Products	0.0583
Rubber & Plastic	0.0600
Financial Mediatory Industry	0.0621
Basic Metals	0.0658
House Clumping, Properties and Pertaining	0.0680
Electrical Machinery and Networks	0.0690
Metal Products Construction	0.0692
Machinery and Equipments	0.0696
Mining	0.0707
Food Stuffs and Chemical Products	0.0739

9. Discussion andConclusion

A chi-square statistical test was performed on received averages of various industries. The results are shown below:

VAR00001			
	Observed N	**Expected N**	**Residual**
.0095	1	1.1	-.1
.0111	1	1.1	-.1
.0119	1	1.1	-.1
.0129	2	1.1	.9
.0135	1	1.1	-.1
.0142	1	1.1	-.1
.0145	1	1.1	-.1
.0155	1	1.1	-.1
.0161	1	1.1	-.1
.0175	1	1.1	-.1
.0178	1	1.1	-.1
Total	12		

Test Statistics	
	VAR00001
Chi-Square	.833[a]
Df	10
Asymp. Sig.	1.000

a. 11 cells (99%) have expected frequencies less than 5. The minimum expected cell frequency is 1.1.

The hypothesis "There is a meaningful difference between industry type and accuracy of shares price forecasting using an artificial neural network" has been examined.

For testing the hypothesis, MATLAB software and the statistical methods mean square error (MSE) and mean absolute error (MAE) have been used. Mean square error and mean absolute error methods have the lowest errors, 0.0095 and 0.0500, respectively, in share price forecasting of the nonmetallic mineral industry and the mean square error method in shares price forecasting of the mining industry (0.0178) and the mean absolute error in share price forecasting of the food industry and chemical products (0.0739) have the highest errors.

Considering the calculated results of chi-square statistical test (0.833), which is less than calculated P (1), we can say with 99 percent certainty that there is a meaningful difference between industry type and accuracy of shares price forecasting using an artificial neural network, so the research hypothesis is confirmed.

Considering the results, it is clear that factors like monthly average price of one ounce of gold, monthly average oil price, monthly average inflation rate, monthly average currency rate and monthly average interest rate affect the accuracy of the share price forecasting of various industries in the Tehran stock exchange. The reason for these factors` effects in various industries is the fluctuations in gold price, oil price, inflation rate, currency rate, and interest rate. The effect is more severe in industries related to these factors and in industries not affected by these factors, the effect less severe.

For instance nonmetallic mineral firms, which are less affected by these factors, have the lowest mean square error and mean absolute error, and it is obvious that mining, food, and chemical product firms, which use advanced technology and whose activity continuance depends on the mentioned fluctuations, have the highest mean square error and mean absolute error.

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