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Predicting Direction of Stock Price Index Volatility Using Genetic Algorithms and Artificial Neural Network Models in Tehran Stock Exchange

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ABSTRACT

Using volatility of stock price index by investor caused prediction of stock price index to be considered as one of the most controversial topics in finance. This study have been conducted using two artificial neural network and hybrid models of genetic algorithm-neural network as a successful model to predict the volatility of stock price index in Tehran stock exchange. Inputs to both models are nine indicators of guidance relating to eleven periods of 6-month from 2005 to 2010. Hybrid model of ANN-GA and ANN model were able to predict the volatility of the stock price index for 11 periods, on average, 96.34% and 89.80% respectively and this study showed that genetic algorithm combination with other models create an effective model to predict artificial intelligence model optimization.

Keywords: Artificial Neural Network (ANN), Genetic Algorithm (GA), prediction, stock price index.

1. INTRODUCTION

It is always risky to make decision on financial matter due to the uncertainty of future. Therefore, one way of helping investors is to provide prediction patterns about total prospect and future state of the company (Valipour, Amin, Zeidi & Akbarpour, 2012). Tendency to increase revenue by investor leads to the use of different standards to predict their earnings. Prediction of stock price index changes are the most important tools to predict which are commonly used by analysts, investors and creditors. The utility of this prediction is that it can help investors to develop effective strategies for buying and selling and to eliminate the potential risk of exchange rate fluctuations through right investment choice, also speculators and the Arbitrages can use these tools for their advantage

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The main issue is for investors to choose true prediction tools of stock price behavior. Despite of different tools to predict, using neural network is considered to be the most effective tools (Kara, Acar Boyacioglu & Baykan, 2011). Accordingly in the study, the model is used to predict the movement of stock price index, so this way, the predictive power of these tools is used in the emerging markets of Iran. Although stock market volatility in Iran is not largely related to the international issues but there are many internal reasons which results to fluctuating stock index. Due to the emerging and developing market in Iran, applying this tools by investors can lead to the development of the market and increase market dynamics (Raei & Talangi, 2004). In this study, has been tried to design a model in order to develop and optimize an artificial neural network. In line with supporting artificial neural network, it can be used of combining artificial intelligence models. In this study, genetic algorithm model has been used to optimize an artificial neural network performance which is one of the most common optimization models in artificial intelligence. As a result, the main purpose of this study is to use these models to predict stock index volatility emerging market of Iran and to recommend its application to the investors and analysts.

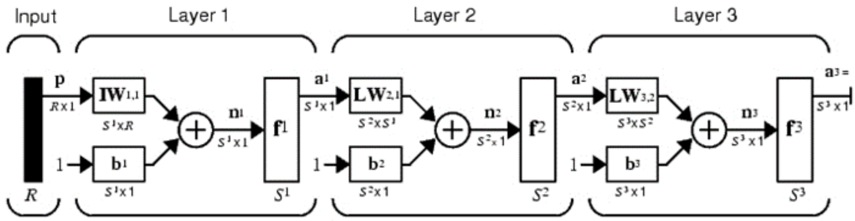
2. LITERATURE

In recent years, some papers have risen dramatically that have examined the time series movements of stock price indices (Kara et al., 2011). These studies, either academic or non-academic try to predict the movement of stock prices or its earnings to discover appropriate trading strategy power based on it (Chen, Leung, & Daouk, 2003). First time, White used neural network to predict in stock market. He was looking at the question of whether the neural movements and changes in stock prices (Schwartz & Whitcomb, 1977), Sinai and Mortazavi (Sinai, Mortazavi & Teymouri Asl, 2005), and Moshiri and Morovat (Moshiri & Morovat, 2006) studied the prediction of stock price index in Tehran stock Exchange and provided some evidences based on chaotic behavior of stock prices index. The results of the study show that neural network model has a better performance than linear models such as ARIMA GARCH models and non-linear models such as ARFIMA for predicting the price index (Moshiri & Morovat, 2006; Sinai et al, 2005). Namazi and Kyamehr (2007) began to study the predictability of stock revenue behavior and also to predict its prediction using artificial neural network. The results showed that time series behavior of daily stock returns is not a random process but the power of learning. Considering the criteria of mean square error, mean absolute error and the value of R, the results have shown that forecasting error scale of artificial neural network model is less than linear regression (Namazi & Kiamehr, 2008). Egeli and Birgul (2003) tried to predict daily stock market index of Istanbul (ISE). The results show that networks predict more accurately than 5-days and 10-days variable average

(Birgul, 2003). Kim (2003) used of support vector machine model and back-propagation neural network to predict daily volatility of stock price index changes in Korea (Kim, 2003). Manish and Thenmozhi (2005) used of non-regular random choice and the support vector machine model for daily prediction for S & P 500 stock Exchange (Manish & Thenmozhi, 2005). Huang and Wang (2005) tried to predict the weekly movement direction (index 225NIKKEL) by support vector machine model, linear discriminant analysis, quadratic discriminant analysis. Research results show that support vector machine model is better than the other models (Huang, Nakamori & Wang, 2005). Mostafa (2010) in a study entitled "forecasting stock price changes of Kuwait by an artificial neural network" investigated and compared between the prediction linear methods, including regression and prediction non-linear methods, including two types of neural networks (Multilayer Perceptron neural network and general regression neural network) among 2001 and 2003, and concluded that neural network models are very useful tools than linear models (Mostafa, 2010). Yaku, Melek and Omer (2011), studied stock price index predictability of the Istanbul Stock Exchange using ANN and SVM by indicators in a research. The results of this research indicate that the prediction of ANN was better than SVM (Kara et al., 2011). Also, Etemadi, Anvary and Farajzadeh (2009) studied corporate bankruptcy prediction using genetic algorithm and result showed that the genetic algorithm has a high ability to predict (Etemadi, Anvary& Dehkordi, 2009).

2.1 Artificial Neural Network

Artificial neural network is a data processing system while consists of a large number of simple processing elements and very connected together (ie, Artificial Nerves) and in its structure has been inspired of brain nose shell. The processor elements have a logical relation with plates usually in layers so that there is a complete or random relationship between the layers (Ghazanfari & Kazemi, 2003). Neurons are the main elements of the brain and alone as a logical processing unit. Brain as an information processing system with a parallel structure is composed of 100 billion interconnected neurons. Neurons are the simplest structural unit of the nervous system (Beale & Jackson, 2010). Over the recent years, more serious efforts have been made to model a natural neurons and considerable progress has been made in this direction (Menhaj, 2005). For modeling an artificial neural network can be used of a mathematical model that describes the properties of a biological system. An overview of neural network is shown in Figure 1.



$a_1=f_1(IW_{1,1}p+b_1)$ $a_2=f_2(LW_{2,1}a_1+b_2)$ $a_3=f_3(LW_{3,2}a_2+b_3)$

$a_3=f_3(LW_{3,2}f_2(LW_{2,1}f_1(IW_{1,1}p+b_1)+b_2)+b_3=y$

Figure 1: Overview of Artificial Neural Networks

Since many factors such as hidden layers, number of hidden layer neurons, the weights corresponding to each layer, conversion functions, normalize the data and the learning algorithm can affect the performance of neural networks, therefore, the best architecture of neural network is achieved by using the experience, trial and error (Ghazanfari & Erkat, 2004).

2.2 Genetics Algorithms

Genetic algorithm is a non-classical optimization method based on biological evolution. GA is a tool by which machines can stimulate mechanism of natural selection by searching in issue space to fine the optimum solution. This model is based on the Darwinian model of evolution that its supplementary calculations were introduced in 1960 by Rychenberg and was presented by John Holland his students (1975) at Michigan University (McKee & Lensberg, 2002). In 1992, John Kazal used this model in inductive programs to perform certain tasks. Genetic algorithms attempt to finalizing search on a population of potential solutions in a parallel way, in every generation or group, chooses the best of them and after birth (using a mutation process with constant probability), it will produce a set of off spring. Regarding to being more suitable persons and individual survival probability in future generations, are among process points. Algorithm is highly flexible and can be the best way for rapid achieving to optimal response. The algorithm for solving the problem propose many solutions, evaluate them using a fitness function, develop with search space trend, present and develop an optimal solution (Tsakonas, 2006).

In nature, mutation is a process in which part of a gene is randomly changed. In the genetic algorithm, probabilities of mutation in chromosomes are considered to be about 0.01 to 0.001. Mutations can adjust while the mutation rate decreases with the increase of popular convergence. In real coding, by mutation limiting to small changes can convert reproduction operator to achieve the converged solution. The following equation is proposed to mutations in the real numbers:

$$x_k' = x_k + \Delta(t, x_k^{max} - x_k) \quad (1)$$

$$x_k' = x_k - \Delta(t, x_k - x_k^{min}) \tag{2}$$

X_k^{max} , the largest allowed value of variable x_k, X_k^{min}, the smallest allowed value of variable x_k. T is the number of produced actual generations theretofore.

$\Delta(t,y)$ is a value between zero and y, and it is calculated by the following equation:

$$\Delta(t,y) = yr(1-(t/T))^b \tag{3}$$

T is the maximum number of generations. B is a parameter greater than 1 and determine the amount of non-uniformity (Rezaee & Ranjbaran, 2009).

2.3 Using Genetic Algorithm to Optimize Neural Network Model

ANN performance is based on the weight training and the values of weights are determined by the network randomly. More accurate values of these are, better network performance will be. In this study, to determine the best weight to improve network performance their values are optimized using genetic algorithms. ANN optimization process by using genetic algorithm is shown in Figure 2.

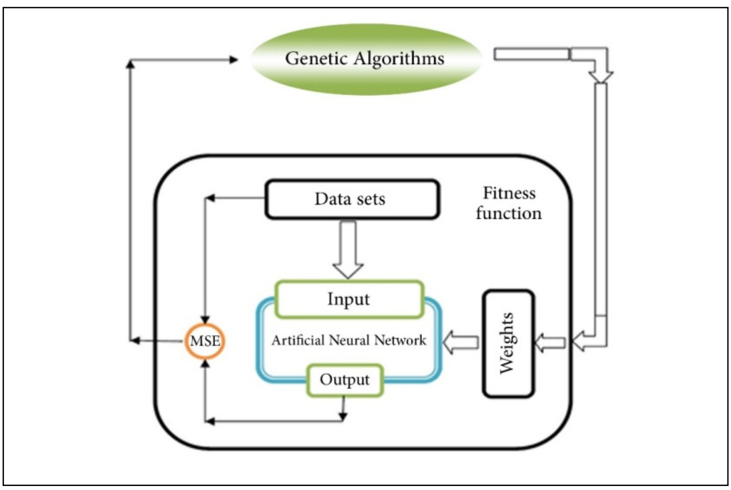


Figure 2: ANN Optimization Process by Using Genetic Algorithm

As can be seen in Figure 2, weights of artificial neural network is composed of genetic algorithm chromosomes. These weights are applied to the network by fitness function. Then desired data set is applied to the network and the mean square error is calculated and is returned to the genetic algorithm as the fitness value or calculated adjustment. Genetic algorithm has parameters to perform optimization operation. These parameters are population size, number of transmitting elites to the next generation, number of generations, rate of mutation operator, rate of composition operator and stop condition. The value of this parameter is specified in the design model section.

3. METHODOLOGY

3.1 Sample Selection

In this study, in order to collect the theoretical foundation of the subject has been used Library Method. Necessary information about research variables has been collected through the Rahavard Novin Database and when necessary go directly through the Tehran stock exchange organization. Arranging and data analysis was done by Excell, Matlab 9 and SPSS software. The purpose of this study is to predict the direction of daily total stock price index volatility based on ANN and hybrid model of ANN-GA and compare them. In this study, raw data include the final price, highest price and the lowest daily stock price index. The input data calculated using raw data and then analyzed to the 11 periods of 6-months. Because used raw data in this study were not provided by the stock exchange before June 2005, has been use of data after June 22, 2005. For statistical population in this study, was used of total stock price index in the Tehran stock exchange in all days that from 6-months periods during 2005/06/22 to 2010/12/21 were active in those days. Table 1 shows the number and date of sample used in each period based on the Tehran stock exchange activity.

Table 1: Number and Date of Sample Used In Each Period Based On the Tehran Stock Exchange Activity

No.	Period	No. of days	No.	Period	No. of days
1	2005/06/22 - 2005/12/21	126	7	2008/06/21 - 2008/12/20	123
2	2005/12/22 - 2006/06/21	118	8	2008/12/21 - 2009/06/21	120
3	2006/06/22 - 2006/12/21	124	9	2009/06/22 - 2009/12/21	125
4	2006/12/22 - 2007/06/21	115	10	2009/12/22 - 2010/06/21	119
5	2007/06/22 - 2007/12/21	124	11	2010/06/22 - 2010/12/21	123
6	2007/12/22 - 2008/06/20	116			

3.2 Data and Descriptive Statistics

Many capitalists and investors fund managers in the stock market generally accept and use a certain criteria for technical indicators or indexed as the signal of future market process (Kim, 2003). A variety of technical indicators are available. Some technical indicators are effective on market process and their better performance (Tsaih, Hsu, & Lai, 1998). In the light of previous studies, it is assumed that various technical indicators may be used as input variables in the construction of prediction models for movement of the stock price index (Chen et al., 2003). By professional study on range of indicators and previous studies, nine technical indicators are selected. Table 2 shows a summary of selected indicators and their formulas. Using the historical data, summary statistics for the selected indicators were calculated and given in Table 3.

Table 2: Selected Indicators and Their Formulas

Name of Indicators	Formulas
Simple 10-day moving average	$\frac{C_t + C_{t-1} + \cdots + C_{t-10}}{10}$
Weighted 10-day moving average	$\frac{\{(n)C_t + (n-1)C_{t-1} + \cdots + C_{t-10}\}}{n + (n-1) + \cdots + 1}$
Momentum	$C_t - C_{t-n}$
Stochastic K%	$\frac{C_t - LL_{t-n}}{HH_{t-n} - LL_{t-n}} \times 100$
Stochastic D%	$\frac{\sum_{i=0}^{n-1} K_{t-i}\%}{N}$
Relative Strength Index(RSI)	$100 - \frac{100}{1 + ((\sum_{i=0}^{n-1} Up_{t-i}/n)/(\sum_{i=0}^{n-1} Dw_{t-i}/n))}$
Larry William R%	$\frac{H_n - C_t}{H_n - L_n} \times 100$
A/D (Accumulation/Distribution Oscillator)	$\frac{H_t - C_{t-1}}{H_t - C_t} \times 100.$
CCI (Commodity Channel Index)	$\frac{M_t - SM_t}{0.015\, D_t}$ $M_t = \frac{H_t + L_t + C_t}{3}.$ $SM_t = \frac{\sum_{i=1}^{n} M_{t-i+1}}{n}.$

	$D_t = \frac{\sum_{i=1}^{n} \lvert M_{t-i+1} - SM_t \rvert}{n}$.

Ct is the closing price, Lt the low price, Ht the high price at time t, LLt and HHt mean lowest low and highest high in the last t days, Upt means the upward price change, Dwt means the downward price change at time t.

Table 3: Summary Statistics for the Selected Indicators

Name of Indicator	**Max**	**Min**	**Mean**	**Standard deviation**
Simple 10-day moving average	18639.04	7976.93	10995.173	2399.486
Weighted 10-day moving average	18759	7978.929	11001.848	2412.374
Momentum	1678.5	-969.41	40.029	325.213
Stochastic K%	100	0	48.625	41.178
Stochastic D%	99.287	0	48.697	36.471
Relative Strength Index (RSI)	99.821	0	49.902	33.083
Larry William R%	724.369	-420.927	58.406	56.436
A/D (Accumulation/Distribution Oscillator)	302.376	-333.333	2.792	116.752
CCI (Commodity Channel Index)	100	0	51.375	41.178

Output variables are classified into two parts; the rise and fall of the stock index. Stock index increase and decrease is quantified by ‘1’ and ‘0’, respectively. According to the structure-function, outputs of models are between ‘0’ and ‘1’. If the output of model be in the range [0.5, 1], it means that the stock price index will increase and if it is less than 0.5, stock index will be reduced. And then these predictions compare with the target data to determine the percentage of correct predictions. In order to cross-validate, has been used 75% of the data for each period for train and 25% of the data to test genetic algorithm network model. In this study attempts to optimize neural network model using optimum genetic algorithm. In this regard a hybrid model was designed to optimize weights of ANN layers using genetic algorithm and then the results of optimized and non-optimized ANN model compare together using genetic algorithms.

3.3 Model Design

In this study, has been used of a back-propagation network that is a type of feed-forward networks. This network is a multilayer network with transfer function of nonlinear and Levenbery-Marquardt learning rule. More results of precious research in the field of stock market forecast shows that to solve this problem, having a hidden or middle layer is sufficient in the network. In the prediction problems, the number of input layer neurons is equal to the number of predicator variables (independent). Therefore, in this study, the number of neurons in the input layer is equal to 9 (number of independent variables). Using the rule of n/2 (n represents the number of neurons in the input layer) for different number of neurons in the hidden layer, along with adjusting other parameters, the conclusion was that five variable neurons in the middle layer can lead to better performance specially in term of popularization ability. Transfer function used in this study is a sigmoid function that its formula is shown as follows:

$F(net) = (1+e^{-net})^{-1}$, (Net weighted sum of input variables of previous layer)(4)

By using this function, the value of output variable will be between 0 and 1. Performance function for network training is considered the Mean Square Error (MSE), its formula is as follows (Kia, 2008):

$$F = MSE = (1/n)\sum^{n}_{i=1}(e_i)^2 \quad (5)$$

To determine the learning rate and frequency numbers of neural network types with various learning rates and frequency numbers have been used of data related to the first period (2005/06/22 - 2005/12/21) randomly. The Table 4 shows the performance of ANN models for ten different types in parameters.

Table 4: Choosing the Best Parameters for an Artificial Neural Network

ANN	n	Lr	epoch	MSE
1	5	0.01	500	0.00597
2	5	0.01	1000	0.00479
3	5	0.01	2000	0.00224
4	5	0.1	1000	0.00397
5	5	0.1	2000	0.00156
6	5	0.1	3000	0.00438
7	5	0.5	1000	0.00774
8	5	0.5	2000	0.00856
9	5	0.7	1000	0.01090
10	5	0.7	2000	0.00947

n:number of neurons in the hidden layer, Lr: learning rate, epoch: training repeat, MSE: Mean Squared Error.

Table 4 shows 10 top structures of artificial neural network. Learning rate changes ranges from 0.01 to 0.9 and for each learning rates has been used of 500, 1000, 2000 and 3000 frequency numbers. Finally, in studying the above table and comparing mean square error, ANN5 is selected as the best ANN structure with mean square error of 0,00156, learning rate of 0,1 and frequency number in 2000.

In the design of genetic algorithms, the size of the population and the elite is considered 25 and 2 respectively; this means that the two best individuals in each generation are transferred without changing to the next generation. The total number of generations is 100. In the stop condition, if there was no change in the fitness value, it can come out of algorithm. The number of chromosomes is determined based on the total number of weight in artificial neural network. These are include: 1) the number of weights in the input layer, 2) the number of middle layer weights, 3) the bias related to the number of middle and output layers neurons. Generally, 56 chromosomes and bias was calculated that constitute the number of genetic algorithm chromosome. To determine mutation operator rate and composition operator rate has been used of random values. The mean square error achieved by network output is a criterion for measuring fitness function. Table 5 shows choosing the best operator rates for the best of fitness.

Table 5: Choosing the Best Parameters for Genetic Algorithms

No.	**Number of Population**	**Composition Rate**	**Mutation rate**	**Best of fitness (MSE)**	**Exit the Algorithms**
1	25	0.7	0.1	0.0002433	51
2	25	0.7	0.2	0.0002754	64
3	25	0.7	0.3	0.0002071	76
4	25	0.7	0.4	0.0001765	69
5	25	0.8	0.1	0.0002138	94
6	25	0.8	0.2	0.0002686	76
7	25	0.8	0.3	0.0003016	65
8	25	0.8	0.4	0.0002947	48
9	25	0.9	0.1	0.0003629	68
10	25	0.9	0.2	0.0003147	81
11	25	0.9	0.3	0.0002873	73
12	25	0.9	0.4	0.0002732	63

Table 5 shows 12 genetic algorithm structures that has been used of 3 combined operator rates (0.7, 0.8 and 0.9) and 4 mutation operator rates (0.1, 0.2, 0.3 and 0.4). In the above table, we can conclude that the best fitness amount 0.0001765 related to mutation operator rate is 0.4and combined operation rate is 0.7 and is emitted from algorithm in 69th generation, and the worst fitness amount 0.0003629 related to mutation operator rate is 0.1 and combined operator rate is 0.9 that is emitted from algorithm in 68th generation. Eventually, combined model 4 is used to anticipate daily stock index volatility.

4. RESEARCH FINDINGS

After training and testing by ANN model in Matlab, the results are derived in two parts of optimized and non-optimized. These results are obtained based on prediction in correct division of stock price index increase or decrease. Table 6 shows the results of ANN and ANN-GA models. Also, Figure 3 shows the comparison chart for two ANN and ANN-GA models.

Table 6: Results of Predicted by the ANN and ANN-GA Models

Period	**(ANN-GA)**			**(ANN)**		
	Train	**Test**	**Total**	**Train**	**Test**	**Total**
1	% 96.81	% 90.63	% 95.24	% 94.68	% 78.13	% 90.48
2	% 98.86	% 86.67	% 95.76	% 92.05	% 80	% 88.98
3	% 100	% 90.32	% 97.58	% 94.62	% 77.42	% 90.32
4	% 100	% 93.10	% 98.26	% 93.02	% 79.31	% 89.57
5	% 98.92	% 87.10	% 95.97	% 93.55	% 77.42	% 89.52
6	% 98.85	% 89.66	% 96.55	% 94.25	% 75.86	% 89.66
7	% 97.83	% 93.55	% 96.75	% 92.39	% 87.10	% 91.06
8	% 100	% 90	% 97.50	% 94.44	% 83.33	% 91.67
9	% 96.81	% 90.32	% 95.20	% 92.55	% 77.42	% 88.80
10	% 97.75	% 90	% 95.80	% 93.26	% 83.33	% 90.76
11	% 98.91	% 83.87	% 95.12	% 91.30	% 74.19	% 86.99
Mean	% 98.61	% 89.57	% 96.34	% 93.28	% 79.41	% 89.80

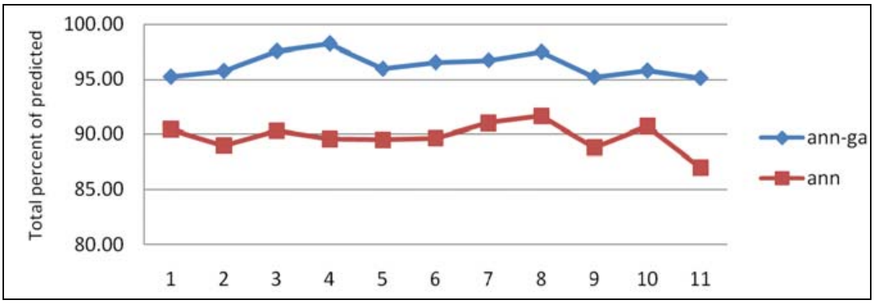


Figure 3: Chart Comparing the Predicted Results of ANN and ANN-GA Models

As seen in Figure 3 and Table 6, in all periods, hybrid ANN-GA model has been better than ANN model to predict volatility for stock price index movement. To present a significant difference between these two models, for all three sample groups of training, testing and total, was used paired comparison test in SPSS 19 software. The outputs of this test for two mentioned models are shown in Table 7 and 8.

Table 7: Statistical Summary of Pairs

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	trainANNGA	98.61	11	1.180	.356
	trainANN	93.28	11	1.138	.343
Pair 2	testANNGA	89.57	11	2.792	.842
	testANN	79.41	11	3.789	1.143
Pair 3	totalANNGA	96.34	11	1.074	.324
	totalANN	89.80	11	1.283	.387

Table 8: Result of Paired Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	trainANNGA–trainANN	5.330	1.510	.455	4.316	6.344	11.706	10	.000
Pair 2	testANNGA–testANN	10.155	3.125	.942	8.056	12.255	10.777	10	.000
Pair 3	totalANNGA–totalANN	6.538	1.205	.363	5.729	7.348	17.995	10	.000

As it is evident from the test results in Table 8, by upper (6,344) and lower (4,316) limit and t statistic (11.706) for pair related to training sample, by upper (12,255) and lower (8,056) limit and t statistic (10.777) for pair related to test sample and by upper (7,348) and lower(5,729) limit and t statistic (17.995) for pair related to total sample, in significance level 0.05, optimized ANN-GA model has a Significant difference than ANN modeling all three sample groups. And this difference show that the genetic algorithm could improve prediction ability of the network by optimizing the weights of the artificial neural network. The exact and appropriate weight determination for artificial neural algorithms is important and effective for anticipation. And in this research, it was shown that can be used of genetic algorithm model to optimize these weights and increase the predictability of total daily stock index volatility by combining artificial neural network model and genetic algorithm model.

5. CONCLUSIONS

Background research indicates that the use of artificial intelligence algorithms to predict the stock market is more efficient than the classical methods. In this research, artificial neural network and hybrid model of genetic algorithm-neural network is used. In this study, predicting the direction of stock price index volatility is done for the 11 periods of 6-months from 2005 to 2010 by genetic algorithm to optimize artificial neural network and the ability of artificial neural network to predict stock market has been increased from %89/80 to %96/24 on average. This combination can help shareholders, investors and creditors in correct decision making. This study, such as other studies, including Mostafa (2010), Chen et al., (2003), Egeli (2003), Moshiri and Morovat (2006) and Sinai and Mortazavi (2005), shows that ANN in predicting the stock index is more efficient than other models. It is hoped that the level of these predicting be improved by combining of other models of artificial intelligence and lead to more correct decision making of users in the stock market.

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