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Full Length Research Paper

Using artificial neural networks for forecasting per share earnings

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Forecasting per share earnings in investments is very important because it is a significant factor in methods of stock evaluation; and in most of these cases, it is a fundamental factor in investing in the stock market. In order to forecast per share earnings using an "artificial neural network with an error backward propagation algorithm" and an "artificial neural network with a genetic algorithm", 61 firms in 7 financial years, from the beginning of 1381 until the end of 1387, with 9 variables (8 input variables and 1 output variable) were chosen; from which 3843 (61*7*9) data point were extracted. The hypotheses are based on the idea that: 1) an artificial neural network with an error backward propagation algorithm is able to forecast the earnings of per share; 2) a neural network with a genetic algorithm is able to forecast the earnings per share; and 3) the neural network with the error backward propagation algorithm has less error in forecasting the earnings per share than the neural network with the genetic algorithm. To test the hypotheses, MATLAB software, the statistical methods of mean square error and mean absolute error were used. The results confirm all hypotheses.

Key words: Earnings per share forecasting accuracy, artificial neural network, error backward propagation algorithm, genetic algorithm, multi-layer perceptron.

INTRODUCTION

Earning is one of the most important and basic items on financial statements; and it draw the attention of financial statement users. Investors, credit givers, managers, employees, analysts, government and other users of financial statement use earnings as a basis for making investment decisions, giving loan, earnings payment policies, firm evaluation, tax calculation decision and other decisions related to companies. The forecasting of per share earnings in investments is very important. The importance of these forecasts depends on the different between the amount of error and the amount of real earnings. The less error, the more accurate the fore-casting (Mashayekh, 2007) The day to day development and spread of computer use in all fields of human science, particularly accounting and investment, has created a field of new technology. Artificial neural networks are one of the latest achievements of this rapid process (Raei, 2003). By copying the human brain, neural networks can discover the relationships among variables, no matter how complicated and non-linear they are. One important applications of this method is to forecast and estimate decisions-making in financial markets. Decision-makers use such networks to maximize efficiency and to minimize the risk of investing in ambiguous conditions (Kuvayev, 1996).

In the past, different forecasting models have been used, the most important of which are linear or multi-sentence regression techniques, voluntary regression, moveable means, the Genkinz and Box model, and structural and time series models, but the weak points of these models is that they do not let the researcher consider the complicated and non-linear factors which are effective for forecasting. However, artificial neural networks can forecast the relationships among variables even when they are very complicated and non-linear.

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In the present research, the main question is related to the multiplicity of earnings forecasting models, and the relative ability of these models to forecast earnings per share on one hand and on the other hand, the ability of models based on artificial neural networks, is it possible to use artificial neural networks for forecasting and what is the ability of the artificial neural network with an error backward propagation algorithm compared to the artificial neural network with a genetic algorithm in this field of study.

LITERATURE REVIEW

In Iran, no study has been done on the subject and its variables. However, some research has been done on financial forecasting using artificial neural networks. In other countries, several studies about using artificial neural networks to forecast earnings have been done. This is discussed subsequently (Wong, 1995).

White used a neural network to forecast in the stock exchange market for the first time. He was looking for the answer to the question: “Are the neural networks able to identify the non-linear rules in time series, unknown rules in changes of asset price and share price change?” White’s goal for presenting this article was to show that a neural network can do this. After White’s study in 1988, neural networks use started in financial fields, and various studies have been done in this field throughout the world.

In other studies, Takoha et al. (1990) established a stock market forecasting system in which a neural network was used.

From 1988 to 1995, on the whole, 213 scientific activities were performed in the field of neural networks in commercial areas. Of these activities, 54 were in the financial field while 2 were in forecasting and time series analysis (Wong, 1995).

Cao and Parry (2009) investigated the models for forecasting earnings per share using neural networks (comparing error backward propagation and genetic algorithms) in 283 firms in different industries. They used a neural network with 7 input variables. The results reveal that the genetic algorithm makes a more accurate forecast of earnings than the error backward propagation algorithm. Zhang et al. (2004) studied models of per share earnings forecasting of neural networks (a comparative analysis of alternative methods) with four kinds of models in 283 firms: one-variable linear models, multi-variable linear models, one-variable neural network and a multi-variable neural network. This research shows that the use of neural network methods provides more accuracy in forecasting than linear forecasting models. Lendasse (2000) tended to use a neural network for the forecasting of stock index. The input data to the network were two kinds of data: introvert and extrovert. The economic extrovert data involved the indexes of international stock price, the rates of exchange (Dollar/ Mark/Yen) the rate of interest (three month and treasury interest rate) the introvert data involved previous index rates. It was concluded that neural networks perform better than linear methods. Garliuskas (1999) attempted to forecast time series of stock market by using a neural network with a calculative algorithm related to kernel function and error forecasting methods. He concluded that forecasting financial time series using a neural network can be more accurate results than using classic statistical models and other models. Chiang et al. (1996) studied neural network methods for forecasting net price in investigation firms. To do this, they used an error backward propagation algorithm a neural network. They compared the results of their studies and network data with finding extracted from traditional techniques of economic evaluation, and found that time series neural networks where there is less data are significantly better than regression methods. In another investigation, which included qualitative factors like political effects associated with quantitative factors, an attempt was made to create a neural network that was a combination of neural network and fuzzy Delphi model. This shape was placed as the basic network for qualitative networks. They tested their model on the Taiwan stock market. Callen et al. (1996) studied the neural network forecasting of three month of accounting earnings in 296 firms whose shares were exchanged in the New York stock exchange and concluded that when paying attention to this matter, three-month earnings is financial, seasonal, and non-linear, and that Brown-Rozeff and Griffin-Watts’ time series models have better forecasting results than neural networks.

Motevaseli and Talebkashefi (2006) did a comparative investigation of artificial neural network capability with the input of technical analysis indexes in order to forecast stock price. The results revealed that, in the case of 30 firms, forecasting the price by ARIMA models presented more meaningful results than by using neural network models. Therefore, it can be stated that linear-models rather than non-linear models (neural networks) have been able to analyze complications of time series of stock price and can be used for the forecasting of stock price. Sinaei et al. (2005) investigated index forecasting in the Tehran stock exchange by means of artificial neural networks. From the neural network designed with data from different intervals of the index, the 3-layer neural network 3-15-1 with an input of three intervals of the index and 299 epochs of training and with MSE = 5710 and r^2 = 0.999 is the best network model for forecasting the stock exchange index. Mahdavi and Behmanesh (2005) investigated the forecasting of the stock prices of investment firms using artificial neural networks. The results of their investigation showed that if a neural network is trained properly, it will be able to identify the relation between the variables and will be effective in forecasting stock prices of investment firms with the least error (0.044). Toloeiashlaghi and Haghdost (2004) examined the models of stock price forecasting by neural networks and compared them with mathematical models of forecasting. This study contradicts observations in previous studies and also the basic theory under investigation. Their result is that in Irankhodro firm, forecasting by regression presents a more suitable and acceptable answer than the model designed by a neural network. Thus, the neural network is not always an appropriate solution to be used in all conditions. Raei and Chavoshi (2003) investigated the forecasting of stock returns in the Tehran stock exchange by means of artificial neural networks and multi-factor models. To evaluate a factorial model, they used linear multi-variable regression, and for neural network, they used MLP architecture with error backward propagation algorithm. The findings showed that these two models were successful in forecasting the stated stock return. This study also revealed the superiority of artificial neural networks over multi-factors models.

H_1: An artificial neural network with an error backward propagation algorithm is able to forecast per share earnings.
H_2: An artificial neural network with a genetic algorithm is able to forecast per share earnings.
H_3: The neural network with the error backward propagation algorithm has less error in forecasting the earning per share than the neural network with the genetic.

RESEARCH METHODS

Based on deductive logic, and from the viewpoint of using models and statistical methods, the mean error square and mean absolute error are used.

Statistical community and sample

The statistical community for this present study were all accepted firms in the Tehran stock exchange that were active in the stock market from the beginning of the year 1381 to 1387. Information from informing firms' software and stock exchange services in the beginning of the year 1381 showed that the number of active firms in the Tehran stock exchange was 300 firms. These firms were in the stock exchange based on their activities in one of the existing 31 industries in the Tehran stock exchange. The method for choosing a suitable statistical sample to be an appropriate representative for the statistical community at hand was the omitting method. Seven criteria were considered and if a company met all criteria, it was chosen as one of the typical firms. The criteria are as follows:

1. The firm's financial period should be finished at the end of Esfand because the stability of typical firms should be observed based on the end of their financial year.
2. The firm should not be an investment firm or a member of finance dealing industries, holdings and banks because their activities depend on other firms' activity or it is separate from other firms; therefore, the accuracy of earnings forecasting in these firms is different from the forecasting framework in other firms.
3. The firm's financial statements should be continuously presented. Firms whose trades have been completely prevented during the research period were deleted from the sample.
4. The firms should be profitable. Firms experiencing a loss were deleted from the sample as a result of their stability and the issue of per share earnings forecasting.
5. The firm should be productive or commercial. Service firms were deleted from the sample, because one of the data sets is net sale in calculating labor force efficiency (net sale / number of employee) and service firms are without sale.
6. The number of the firm's employees must be listed in the explanatory notes. Because one of the data sets involved in the calculation of labor force efficiency (net sale / number of employee) requires the number of employees.
7. The firm should not be a member of a firm group because groups are the result of combination and division, and the forecasting of per share earnings can be influenced.

After applying all the aforementioned criteria, our observations totaled 427 firm-years and included 14 different industries.

Variables

Predicting variables (independent)

1. Relation of rial value of inventory to number of common shares.
2. Relation of commercial received accounts to number of common shares.
3. Relation of non-commercial received accounts to number of common shares.
4. Relation of capital expenditure (increase in cost of tangible fixed assets during the financial year) to number of common shares.
5. Relation of gross earnings to number of common shares.
6. Relation of administrative expenses and sales to number of common shares.
7. Effective tax rate.
8. Labor force productivity logarithm (Cao, 2009).

Predicted variable (dependent)

Earnings per share: Table 1 shows how the variables were extracted and calculated.

Hypotheses-testing process

Artificial neural network models are multi-layer perceptron with sigmoid transfer function, training error backward propagation algorithms and genetic algorithms. First, the data were entered in Excel, and after doing the necessary calculations and finding the most and the lowest value, values were normalized according to the following formula:

$$\frac{\text{The lowest value} - \text{All value}}{\text{The most value} - \text{The lowest value}}$$

After normalization, the data were put between 0 and 1, that is, sigmoid dimension function. The neural network design consists of 8 input layers and 1 output layer. To calculate the hidden layer, the following formula was used to determine what 24 hidden layers were made (Cao, 2009).

Number of hidden layers = ½ (number of input variables + number output variables) + √number of learning patterns

$$\text{Number of hidden layers} = \tfrac{1}{2}(8+1) + \sqrt{366} \approx 24$$

Therefore, the neural network model in MATLAB software was

Table 1. Methods of calculating and extracting the variables.

	Row	Variable	Data	Source	Calculation method
Predicting variables (independent)	1	Relation of Rial value of inventory to number of common shares	Inventory and common shares number	Balance sheet	$\frac{\text{Real value of inventory}}{\text{Number of common shares}}$
	2	Relation of commercial receivable accounts to number of common shares	Receivable accounts and common shares number	Balance sheet	$\frac{\text{Commercial receivable accounts}}{\text{Number of common shares}}$
	3	Relation of non-commercial receivable accounts to number of common shares	Non-commercial receivable accounts and common shares number	Balance sheet	$\frac{\text{Non-commercial receivable accounts}}{\text{Number of common shares}}$
	4	Relation of capital expenditure(increase in cost of tangible fixed assets during the financial year)to number of common shares	Capital expenditure and common shares number	Explanative notes of financial statement	$\frac{\text{Capital expenditure}}{\text{Number of common shares}}$
	5	Relation of gross earnings to common shares number	gross earnings and common shares number	Income statement and balance sheet	$\frac{\text{Gross earnings}}{\text{Number of common shares}}$
	6	Relation of administrative expenses and sales to common shares number	administrative expenses and sale and common shares number	Income statement and balance sheet	$\frac{\text{Administrative expenses and sale}}{\text{Number of common shares}}$
	7	Effective tax rate	Tax rate	Income statement	$\frac{\text{Tax}}{\text{Earnings before tax reduction}}$
	8	Labor force productivity logarithm	Net selling and number of employee	Income statement and explanative notes of financial statement	$\text{Log}\ \frac{\text{Price of total net sale}}{\text{Total number of employee}}$
Predicted variable (dependent)	1	Per share earnings	Per share earnings	Income statement	$\frac{\text{Net earnings}}{\text{Number of common shares}}$

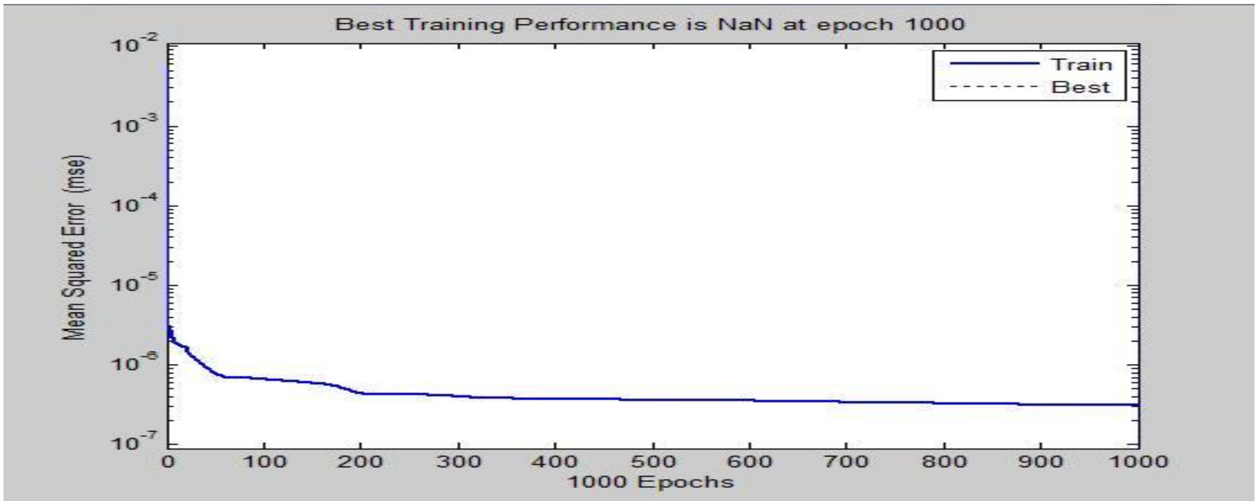

Figure 1. Situation of training network using an error backward propagation algorithm.

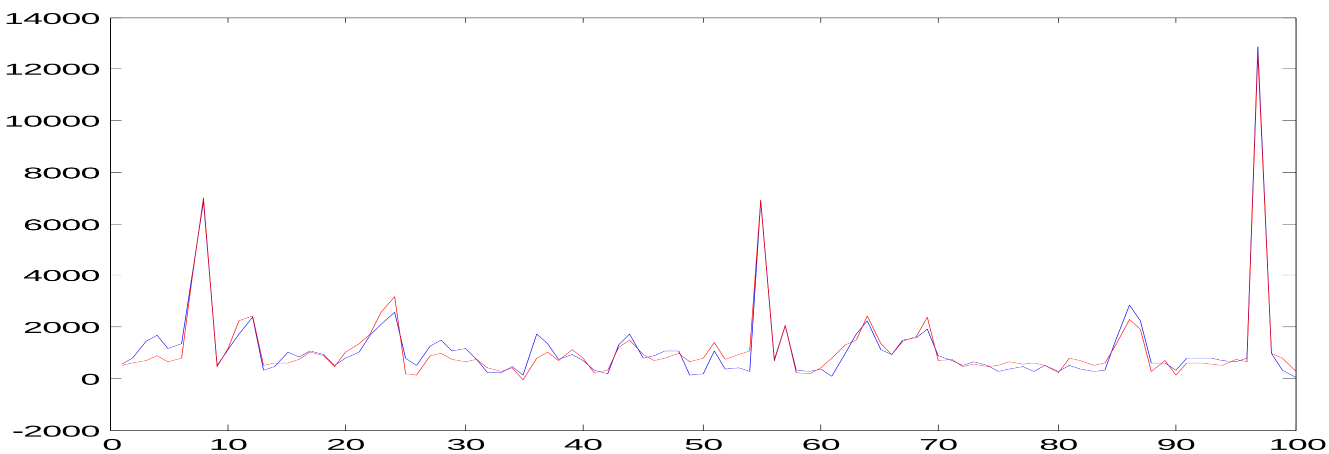

Figure 2. The state of training data and forecasting data movement in artificial neural network with error backward propagation algorithm.

designed as 8-24-1, that is, 8 input layers, 24 hidden layers, and 1 output layer. From 3843 collected data point, 86% from financial years 81 to 86 were considered training data and 14%, from year 87, as forecasting data.

Forecasting of per share earnings using an artificial neural network with an error backward propagation algorithm

Figure 1 shows the results of the training network with epoch number 1000. The error rate has been reduced to about $10^{-6.5}$ and has reached a stable limit. Thus more training than necessary has been prevented.

The state of the training data and forecasting data movement in the artificial neural network with an error backward propagation algorithm is presented in Figure 2.

The mean square error and mean absolute error in forecasting per share earnings using the artificial neural network with error backward propagation algorithm is shown in Table 2. As shown in Table 1, the mean square error (MSE) in forecasting per share earnings using the artificial neural network with error backward propagation algorithm is 3.16×10^{-7} and the mean absolute error (MAE) is 3.53×10^{-5}. Therefore, considering that the mean square error and mean absolute error are low, the artificial neural network with error backward propagation algorithm can forecast per shares earnings.

Forecasting of per share earnings using an artificial neural network with a genetic algorithm

Figure 3 shows the situation of the training network using a genetic algorithm. The state of the training data and forecasting data movement in the artificial neural network with a genetic algorithm is shown in Figure 4.

The mean square Error and mean absolute error in earnings per share forecasting using the artificial neural network with a genetic algorithm is presented in Table 3. As shown in Table 2, the mean

Table 2. Mean square error and mean absolute error in forecasting of per share earnings using artificial neural network with error backward propagation algorithm.

Description	MSE	MAE
Forecasting per share earnings in the year 1387 using the artificial neural network with error backward propagation algorithm (BP)	3.16×10^{-7}	3.53×10^{-5}

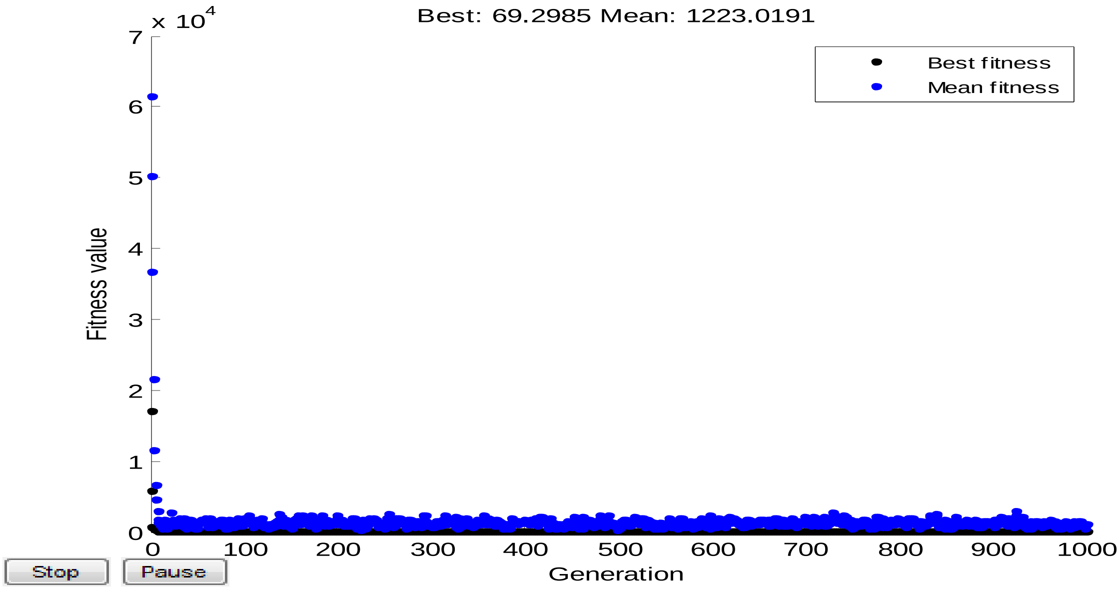

Figure 3. Situation of training network using a genetic algorithm.

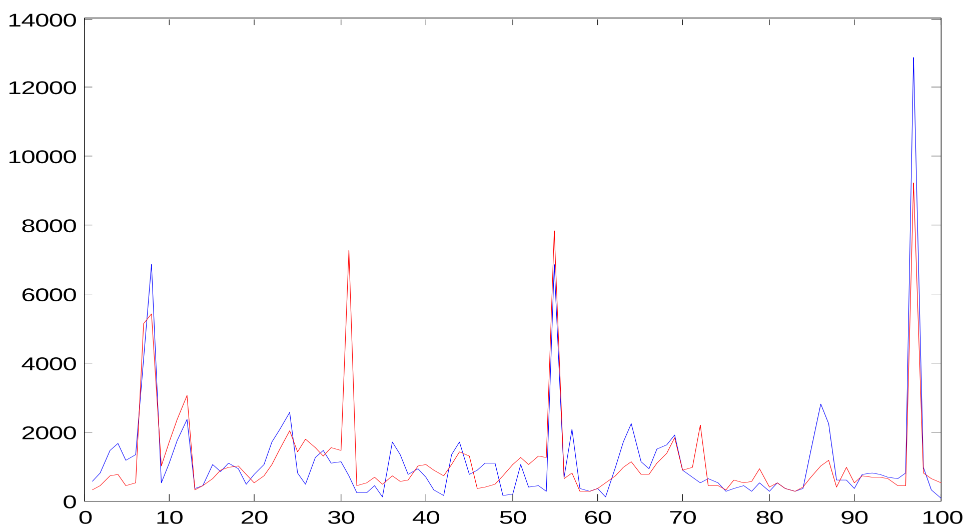

Figure 4. The state of training data and forecasting data movement in the artificial neural network with genetic algorithm.

square error (MSE) in forecasting of per share earnings using the artificial neural network with a genetic algorithm is 5.26×10^{-5} and the mean absolute error (MAE) is$2\times10^{-3.}$ Therefore, considering that the mean square error and mean absolute error are low, the artificial neural network with genetic algorithm can forecast per shares earnings. Table 4 compares the results of using artificial

Table 3. Mean square error and mean absolute error in earnings per share FORECASTING using the artificial neural network with genetic algorithm.

Description	MSE	MAE
Forecasting of per share earnings in 1387 using the artificial neural network with genetic algorithm (GA)	5.26×10^{-5}	2×10^{-3}

Table 4. Comparison of the accuracy of per share earnings forecasting an artificial neural network with an error backward propagation algorithm versus a genetic algorithm.

Description	MSE	MAE
Forecasting of per share earnings of the year 1387 by artificial neural network with error backward propagation algorithm (BP)	3.16×10^{-7}	3.53×10^{-5}
Forecasting of per share earnings in 1387 by artificial neural network with genetic algorithm (GA)	5.26×10^{-5}	2×10^{-3}

neural networks with each of the two types of algorithm. Therefore, the neural network with the error backward propagation algorithm has less error in forecasting the earnings per share than the neural network with the genetic algorithm.

Conclusion

Three hypotheses were tested in the present study. 1) An artificial neural network with an error backward propagation algorithm is able to forecast per share earnings. 2) An artificial neural network with a genetic algorithm is able to forecast per shares earnings. 3) The neural network with the error backward propagation algorithm has less error in forecasting the earnings per share than the neural network with the genetic algorithm.

The hypotheses were tested using MATLAB software, and mean square error (MSE) and mean absolute error (MAE) statistic. The mean square error in forecasting per share earnings using the artificial neural network with error backward propagation algorithm was 3.16×10^{-7} and the mean absolute error was 3.53×10^{-5}.

The mean square error in forecasting of per share earnings using the artificial neural network with a genetic algorithm was 5.26×10^{-5} and the mean absolute error was 2×10^{-3} .

The findings reveal that in general, the error rate, whether with an error backward propagation algorithm or a genetic algorithm, is low; and that therefore, an artificial neural network is definitely useful for forecasting per share earnings. However, from the comparison between the two training algorithms, it was observed that the artificial neural network with the error backward propagation algorithm is more accurate and has less error than the artificial neural network with a genetic algorithm.

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