

P/E Modeling and Prediction of Firms Listed on the Tehran Stock Exchange; a New Approach to Harmony Search Algorithm and Neural Network Hybridization

Mozhgan Safa, Hossein Panahian *

Department of Accounting, Islamic Azad University, Kashan Branch, Kashan, Iran

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Abstract

Investors and other contributors to stock exchange need a variety of tools, measures, and information in order to make decisions. One of the most common tools and criteria of decision makers is price-to earnings per share ratio. As a result, investors are in pursuit of ways to have a better assessment and forecast of price and dividends and get the highest returns on their investment. Previous research shows that neural networks have better predictability than statistical models. Thus, Harmony Search algorithm and neural network have been used in this work, since achieving the best forecast is more likely. For this purpose, a sample consisting of 87 companies has been selected from those listed at the Tehran Stock Exchange over a 10-year period (2006-2015). The results show the high accuracy of the designed model that predicts the price-to-earnings ratio at the stock exchange by hybridizing the balanced search algorithm with neural network.

Keywords

Harmony Search, Price to earnings ratio, Fundamental Analysis, Panel data econometrics, RBF neural network.

* Corresponding Author, Email: panahian@yahoo.com

Introduction

Doing essential analyses and making predictions about dividend, stock price, price-to-earnings ratio as well as data that stock exchange provide for shareholders are very crucial to market transparency. The ability to provide correct prediction and estimation with the least error of the p/e ratio can equip management with a useful tool for making financial decisions. Since any decision by company's senior management influences firm's performance and ultimately its value and stock price, and that the managers are always at risk in this area, having a model that can accurately estimate this ratio can be a valuable contribution to firm management.

Thus, picking a prediction method from a variety of methods is a crucial step; that is, given the informed calculation of prediction errors and their comparison, we can choose an appropriate and desirable method.

In the past, there were a variety of predicting models, the most important of which were linear regression or polynomial regression, auto regression, moving average, Box-Jenkins models, as well as the structural and time series models (Jondaghi et al., 2010). However, these models have weaknesses that do not allow researchers to consider complex and non-linear factors affecting a forecast. In recent decades, a new method, known as artificial intelligence, has come into existence, which is able to detect relations between variables, albeit complex and nonlinear, by adapting the process of human brain learning (Sadeghi, 2011).

Therefore, thanks to the high ability of neural networks in learning complex and nonlinear relations, it has been increasingly used in various fields of science. As for its important application, we can refer to the forecast and optimization of decision-makings in financial markets, which allows decision-makers to make use of it in an attempt to maximize returns and minimize the risk of making investment under unclear circumstances. The results of studies into the prediction of stock price indicate that neural networks outperform previous models (Yadav et al., 2013).

The use of more sophisticated computing tools and algorithms such as neural networks for modelling nonlinear processes that leads to stock price and trend is a better response to statistical methods.

Furthermore, the optimization of input variables, using metaheuristic methods such as Harmony Search algorithm etc., in such predicting tools can enhance the achievement of an optimal result and appropriate response (Ramezani et al., 2011).

Theoretical foundations and review of literature

Most decisions made by the management and investors depend on a state of future prediction. One of the areas that today's forecast is of particular importance is economic and financial matters, particularly in capital markets. It is evident that the best ways of forecast for specified conditions are not the precise ones but a method that meets requirements and desirable precision with the lowest cost (Nofaresti, 2011).

Research shows that it is feasible to forecast a variable more easily and with fewer errors if one is able to detect the process of generating the data of that variable. Although advanced linear models entail proper forecast in midterm and short-term periods, studies on capital market have indicated that stock behavior does not follow a single linear pattern, and linear models just exhibit part of stock behavior in the market (Moshiri and Morovat, 2006). In this case, the existence of a nonlinear dynamic system actually makes existing models uncertain as to market behavior. Thus, forecasting data that follow this system requires smart and advanced tools such as neural networks. As a smart system, the networks can detect nonlinear relations between inputs and outputs according to dataset, and identify fundamental links between them.

Such nonlinear methods as neural networks have multiple important advantages compared to statistical models such as linear regression. The drawbacks to linear regression vis-à-vis nonlinear methods (e.g. neural networks) include; (DeTienne et al., 2003)

- The linear nature of regression; an important disadvantage of linear regression is that it does not offer any direct indicator as to whether the data is best presented in linear state. Given the nature of social sciences, linear statistical analysis is not preferable in most cases.

- The model specification required in advance; the use of regression models requires the specification of the base model. This helps to solve the problem easier but entails significant guesswork.

- The assumptions of regression: the function of linear regression models depends on various assumptions such as the lack of multiple linear relations and the normal distribution of the remainders.

- Lack of adaptability: multiple-regression is not adaptive, in the sense that model components cannot be identified by guesswork (Setayesh and Kazemnejad, 2015).

Adabaei et al. (2012, a) forecasted share prices using data mining technique and artificial neural networks. They used a mixed method (technical and fundamental analysis) to improve existing methods. The fundamental analysis variables include P / E, news and rumors, book value of share, and financial status. The results indicated a significant improvement in the mixed approach compared to technical analysis method; likewise, prediction with a hybrid approach as a guide to the action of traders and investors was shown to be appropriate in the improvement of the quality of their decision making.

Adabaei et al. (2012, b) examined the effect of the hybrid market indices for forecasting stock prices. The market indicators included technical, fundamental variables, and expert opinions as inputs to the artificial neural network; fundamental variables included P/E, ROA and ROE. The empirical results compared to the published stock data of companies Dell and Nokia from New York Stock Exchange show that the proposed algorithm is effective in improving the accuracy of stock price forecast.

Given that various stock pricing methods such as technical analysis, fundamental analysis, time series analysis, and statistical analysis are not taken as predictive tools, Budhani et al. (2012) sought out a method to replace these methods. In this regard, artificial intelligence and artificial neural networks are a promising way of identifying covert and overt patterns of the data and can be used as a suitable way to predict stock market. Input data include opening and closing price, stock trading volume, and P/E ratio. The training algorithm uses predictive neural networks and the results indicate satisfactory performance in reducing the errors of real and expected results.

Vanjova et al. (2014) investigated an artificial neural network model for predicting stock prices in the stock market. The results

showed that the model is able to replace traditional stock price forecasting methods.

Using a SVM, backup vector machine, and box theory, Vercher and Bermudz (2015) worked out the upper and lower bounds of stock price fluctuations to show that if the current stock price is higher than the upper bound of the stock, a buy signal is given, and if the price is lower than the lower bound of the share, sales signal is given. With the study of macroeconomic variables in Belgium, Lycares and Metahetis (2015) came up with a model for forecasting stock prices in the Belgian Stock Exchange during the period 2000-2015.

Neural network algorithm

A neural network algorithm generally has the same structure; each category represents an artificial neural cell. The data enters the network via input layer nodes. These inputs are transferred to hidden layer nodes through interfaces and leave the output layer nodes through different layers. If a network has n nodes on input edge, and L_1 is neuron in the hidden layer, L_2 neuron in the second hidden layer and K neuron in output layer, it is demonstrated as $n - L_1 - L_2 - k$ network (Russel and Norowig, 2012).

Harmony Search algorithm

Today, evolutionary algorithms such as GA algorithm, HS search algorithm, imperialist competitive algorithm (ICA) and PSO (Particle Swarm Optimization) are very popular. An important feature of such algorithms is that the closest solution to the problem can be found for a wide range with no analytical solution.

Harmony Search algorithm is a new evolutionary and meta-heuristic method based on music process, which begins with a generation of solution vectors in the form of algorithm memory and search in the context of problem solving and moves toward the optimal space according to the probabilistic approach. Firstly, proposed by Geem et al. in 2001 by drawing on the process of composing music, the Harmony Search (HS) is generally built on natural behavior of musicians in generating the best harmony (Lee et al., 2005). Harmony Search begins with a generation of solution vector and is used for a newer generation of selection process, but unlike genetic algorithm, in which two chromosomes are used to

produce one chromosome or a new solution vector, we improvise a new solution from existing solution vectors in the memory. As for the advantages of the algorithm, we can refer to rapid convergence due to its proper structure. (Gao et al., 2015).

Steps of problem solving by HS algorithm

In this algorithm, each solution is called a harmony and is represented by an N-dimensional vector. The algorithm has three main phases: 1) first generation (initialization); 2) the improvisation of the New Harmony vector; and 3) updating the memory of the algorithm.

According to the first phase, an early generation of harmony vectors is randomly created and stored in harmony memory size (HM). In the second phase, a new harmony vector (new solution) is created using memory consideration rules, step matching, and random re-generation of existing solutions in the memory of the algorithm.

Description of the solution method

The steps above include: step 1) initialize algorithm parameters; step 2) initialize the harmony memory (HM); step 3) improvise a new solution vector; step 4) update the harmony memory; and step 5) check stopping criterion.

The algorithm parameters are set in the first place. HS algorithm parameters include harmony memory size (i.e. the number of solution vectors in the memory), harmony memory consideration rate, pitch adjustment rate, bandwidth, the number of improvisations (the condition for stopping this solution method is that those variables that fail to help us get optimal solutions). In the second phase, a swarm of solvable vectors as shown in Fig. 1 are registered in the matrix of harmony search algorithm memory that include HMS vector in a random fashion. Components of each solution vector must be within its range.

Step 3: in this phase, the vector of a new solution is improvised. According to the following quasi-code, the initial component is generated in order to improvise a new solution; this iterates up to the Nth component of solution vector. The process of improvising each component is in accordance with rule 3. Rule 1 (Memory consideration) says if the value of Rand (a random value between zero and a distribution function is a constant probability) is less than that of

HMCR, the value of the i^{th} component of the new solution is initialized by one of the existing solutions in the memory in a random fashion, or else as with rule 3 (selection random), the value of the component is randomly initialized from the specified range of that component. Rule 2 of the algorithm (adjustment pitch) is used when rule 1 is implemented, in that a change has triggered the value of the component of the new solution with respect to the value of BW, if the rand value is less than that of PAR. The i parameter in Fig. 2 is the i^{th} component of a harmony solution; that is, it iterates separately in a loop for each iteration for the total components of each solution.

1	x_1^1	x_2^1	. . .	x_N^1	$f(x_1)$
2	x_1^2	x_2^2	. . .	x_N^2	$f(x_2)$
.
.
HMS-1	x_1^{HMS-1}	x_2^{HMS-1}	. . .	x_N^{HMS-1}	$f(x_{HMS-1})$
HMS	x_1^{HMS}	x_2^{HMS}	. . .	x_N^{HMS}	$f(x_{HMS})$

Fig. 1. Algorithm memory with HMS of solution vector

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for (j=1 to n) do
  if (r1 < HMCR) then
     $X_{new}(j) = X_a(j)$  where  $a \in (1,2,\dots,HMS)$ 
    if (r2 < PAR) then
       $X_{new}(j) = X_{new}(j) \pm r_3 \times BW$  where  $r_1, r_2, r_3 \in (0,1)$ 
    endif
  else
     $X_{new}(j) = LB_j + r \times (UB_j - LB_j)$ , where  $r \in (0,1)$ 
  endif
endfor
    
```

Fig. 2. quasi-code of improvising new solution in harmony

Step 4; if the value of the objective function, derived from the new solution vector, is better than that of the objective function of the worst solution in the memory, it will be replaced with its replacement in the harmony memory (i.e. memory is updated). In step 5, the above process continues until the condition for stopping, i.e. the number of new vectors generated NI, is satisfied. Each of the steps described above is run to get results from all of the listed variables. Next, the optimal variables are specified and will be used in the artificial neural network. It should be noted that an optimal variable is a variable that predicts the objective variable with the highest probability and least error, which a fig between 0 and 1 is assigned to variables in the harmony search algorithm.

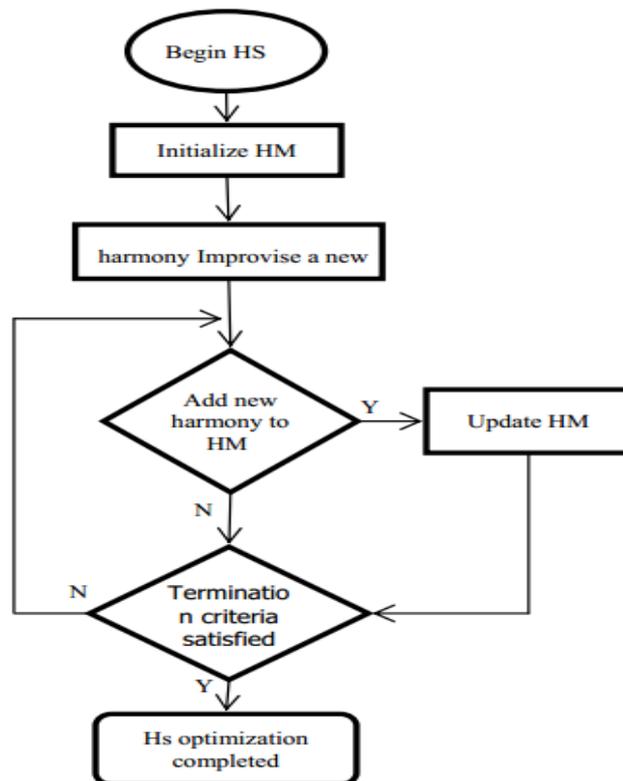


Fig. 3. How the harmony search algorithm works

Having generated the New Harmony vector \vec{X}_{new} , HM needs to be updated, in the sense that the objective function of \vec{X}_{new} is compared with the objective function of the worst member in the memory \vec{X}_w . If the objective function of \vec{X}_{new} is better than that of \vec{X}_w , \vec{X}_{new} is replaced with \vec{X}_w . That is, \vec{X}_w is removed from the memory and \vec{X}_{new} is the new member of the memory. In the end, steps 3 and 4 iterate until stopping condition is met so that an optimal solution is obtained (Jalili et al., 2013).

In neural networks, an attempt is made to build a structure similar to the biological structure of human brain and body's neural network, so that it has the power of learning, generalizing and decision making just like the brain. Artificial neural networks do not need a mathematical model, because the networks gain experience just like human being and then they generalize the experiences. Today, the networks are used in many cases such as prediction (approximation), estimation, model specification, classification, and clustering, and have taken on practical usage on a wide variety of industries (Russel and Norwig, 2012). In general, designing neural network for problem solving and studying the link between phenomena can change our thinking pattern about various subjects and lead to new insights and algorithmic improvements (Brayton and Celina, 2012).

Research empirical background

In econometrics, a variety of models have been introduced to forecast time series with or without long memory, but the use of fuzzy and meta-heuristic models for prediction dates back to less than a decade ago.

Following these models, further research has been done, one of which is the problem of determining appropriate intervals for the application of prediction models. In his paper, Horag points out that different intervals can bring about different prediction results, so it is required to determine appropriate intervals in order to obtain better predictive accuracy. To achieve such a big goal, Horag used meta-heuristic algorithms for the first time ever.

By studying Harmony Search algorithm and applying it to the optimization problems, Taghilo and Teimoru (2011) indicated that HS method outperforms genetic algorithm in terms of memory usage and convergence rate to a problem solution.

Aflatoni (2015) studied the determinants of the level of inventory holding of materials and their ranking by using decision tree and neural network algorithms. Their findings indicated the better performance of neural networks compared with the decision tree algorithm and its more ability in ranking.

Mashayekh et al (2013) investigated the predictability of PEG ratio vis-à-vis P/E ratio in order to determine stock price in firms listed on the Tehran Stock Exchange. They used another criterion, which is known as PEG ratio, which has been proposed as an optimal tool of stock specification in recent years. PEG ratio is defined as price to earnings per share divided by its expected growth rate. This ratio is based on P/E ratio and considers the growth prospect of a share. Using 215 firm-year data during 2002-2010, they demonstrated that P/E ratio is more stable than PEG, and stock price forecast is more accurate with PEG model.

Using HS model optimization in a dynamic environment, Taheri (2012) indicated that the algorithm has better performance and accuracy than other models among criteria used for the optimization of financial criteria.

Jansky and kalassky (2010) chose optimal parameters in designing the neural network algorithm in order to predict stock price movement. The result showed that the accuracy of the algorithm is over 60% for the prediction of stock price movement. Given that various methods for stock price prediction such as technical analysis, fundamental analysis, time series analysis and statistical analysis as tools of constant prediction could not be accepted as tools of constant prediction, Bohani et al. (2012) sought ways to replace them. In this vein, artificial intelligence and artificial neural networks are promising ways of identifying unknown and hidden patterns in data and can function as proper ways of predicting stock market.

Adebiyi et al. (2012, a) predicted stock prices using data mining techniques and artificial neural networks. They used a mixed method (technical and fundamental analysis) in order to improve existing methods. the variables of fundamental analysis included P/E ratio, news and rumors, book value and financial status. The results showed a significant improvement in the hybridized method vis-à-vis technical analysis. Likewise, prediction with the hybridized approach was considered appropriate as a guide to traders and investors in the improvement of their decision-making quality.

Wanjawa et al. (2014) studied an artificial neural network model for predicting stock price at a stock exchange. The results showed that the model is able to replace traditional methods of stock price forecast.

Research question and hypothesis

The main question of this research is how meta-heuristic models such as Harmony Search are used for the optimization of neural networks in order to explain and present the models of forecasting financial and economic variables like P/E. Given the research goals and to provide answer to the research question, the following hypothesis is presented.

Hypothesis: there is the possibility of designing and explaining the P/E model by using HS algorithm in the optimization of neural network model variables.

Research methodology

The present research is an applied study by purpose and an analytical-mathematical inquiry by method. In this study, using the techniques of HS algorithm, we identified and ranked the determinants of the price-to-earnings ratio. For the collection of required data, the financial statements of firms allowed to trade on the Tehran Stock Exchange during 2006-2015 were used. In this research, for sample selection, some firms were systematically excluded from among all available firms.

According to Cochran's sample calculation formula, from among the 112 available firms we obtained 87 firms at the 5% error level.

Research variables

In this research, the following variables are used to optimize and select the best variables of prediction and their application in neural networks. In addition, variables used in relation to Price-to-earnings ratio in various studies (Yildiz and Yezegel, 2010; Vanstone et al., 2004) have been utilized.

In case of a high correlation between variables, a synthetic variable (factor analysis) is used as per values (Jalliff, 2002; Salimifar, 2010), and macroeconomic variables used in this research include oil revenue, exchange rate, gold coin rate, inflation rate and the volume of money (Slamloian and Zare, 2006; Karimzadeh, 2006; Saeedi and Amiri, 2007; Najjarzadeh, et al., 2009; Pirae and Shahsavari, 2009; Torabi and

Homan, 2010; Sajjadi and Sofi, 2010; Amiri, 2013), which were gathered from economic reports, balance sheets, and economic indicators presented on the Central Bank website over the period 2006-2013.

Table 1. Introduction of research variables

Sum of current asset	Current assets include cash and other cash equivalents and assets whose ability of conversion to cash is great.
Sum of debt	(sum of current debt + long-term debt)
P/E	Income/price
Book value	Number of shares/equity
P/S	Net sales/prices
P/BV	Book value/price
BV/M	Market value/book value
Stock return	$100 \times (\text{base price}/(\text{base price} - \text{price of the day}) + \text{dividend per share} + \text{pre-emptive right, bonus shares})$
Current ratio	Current debt/ current asset
Quick ratio	Current debt/ quick asset
Current debt-to-asset ratio	Current debt/ equity
Debt-to-capital ratio	Equity/ total debt
Debt-to-asset ratio	Total asset/ total debt
Interest coverage ratio	Cost of interest/ earnings before interest and taxes
Cash asset turnover	Quick asset/ net sales
Current asset turnover	Current asset/ net sales
Tangible fixed asset turnover	Tangible fixed assets/ net sales
Gross profit margin	Net sales/ gross profit
Operating profit margin	Net sales/ operating profit
Net profit margin	Net sales/ net profit
ROE	Equity/net sales
ROA	Total assets/ net sales
EPS	Number of shares/ net profit
Oil revenue ¹	Include income from oil exports
Gold coin price ²	Price of Bahar Azadi gold coin
Money volume ³	Banknotes and coins + demand deposit + saving deposit
Exchange rate in free market ⁴	Include rates used in unofficial (non-governmental) markets for exchanging Iranian rials and different types of currencies.
Inflation rate based on consumer index ⁵	A measure of fixed and specified price changes in goods and services of urban households

1. Annual oil revenue (million rials)

2. Average annual price of a Bahar Azadi Gold coin

3. Annual money volume (billion rials)

4. Annual average (dollar-rials)

5. Annual average (% of average annual change in proportion to base year)

Having made the prediction about the price-to-earnings ratio, the criteria RMSE¹, MAE², MAPE³ are used for the calculation of prediction error (Thawornwong and Enk, 2004; Arabi, 2005; Moshiri and Morovat, 2006; Ebadi, 2009; Puspanjali et al., 2012).

$$RMSE = \sqrt{\sum_{t=1}^n (\hat{y}_t - y_t)^2 / n}$$

$$MAE = \sum_{t=1}^n |\hat{y}_t - y_t| / n$$

$$MAPE = 100 \sum_{t=1}^n \left| \frac{\hat{y}_t - y_t}{y_t} \right| / n$$

(6)

Research findings

Optimal variable is a variable with maximum probability and minimum error prediction objective variable. The solution is demonstrated in Harmony Search as a decimal number between zero and 1, where the more a variable can predict an objective, the closer to one it will be.

Given the results of HS test of the variables with the highest predictability of the target variable, the priorities ranked first to fifth, i.e. stock return, stock price-to-book value ratio, net sale-to-price ratio, ROA, and EPS, while the market value/book value, the macroeconomic variable money volume, operating profit margin, ROE, and current asset turnover ranked sixth to tenth. From existing variables, the ten variables that predict the target variable of the study (price-to-earnings ratio) based on HS algorithm with greater possibility were utilized.

1. Root Mean Squared Error
2. Mean Absolute Error
3. Mean Absolute Percentage Error

Table 2. Results of HS algorithm in data optimization

Row	Variables	Probability of prediction	ranking
1	Sum of current asset	0.222	20
2	Sum of debt	0.258	16
3	Book value	0.364	11
4	P/S	0.655	3
5	P/BV	0.727	2
6	BV/M	0.552	6
7	Stock return	0.731	1
8	Current ratio	0.311	14
9	Quick ratio	0.307	15
10	Current debt-to-capital ratio	0.316	13
11	Debt-to-capital ratio	0.238	18
12	Debt-to-asset ratio	0.321	12
13	Interest coverage ratio	0.157	25
14	Cash asset turnover	0.235	19
15	Current asset turnover	0.372	10
16	Tangible fixed asset turnover	0.217	21
17	Gross profit margin	0.178	23
18	Operating profit margin	0.423	8
19	Net profit margin	0.188	22
20	ROE	0.401	9
21	ROA	0.631	4
22	EPS	0.561	5
23	Oil revenue	0.114	26
24	Gold coin price	0.015	27
25	Money volume	0.529	7
26	Exchange rate in free market	0.245	17
27	Inflation rate based on consumer index	0.164	24

Statistical tests of the hypothesis

Table 3. standard Error Test

VARIABLE	number	Standard error of skewness coefficient	Standard error of kurtosis coefficient
1var	870	0.087	0.195
2 var	870	0.087	0.195
3 var	870	0.087	0.195
4 var	870	0.087	0.195
5 var	870	0.087	0.195
6 var	870	0.087	0.195
7 var	870	0.087	0.195
8 var	870	0.087	0.195
9 var	870	0.087	0.195
10var	870	0.087	0.195

Table 4. Statistical indicators of predicted residual values

statistic	Number of observation	Standard deviation	Mean	max	min
Predicted value	870	4173.55574	3918.7824	37715.9570	-17632.4219
residual	870	3813.46724	0.000	35285.08891	-1883.19727
Standardized predicted value	870	1.000	0.000	7.373	-5.335
Standardized residual	870	0.973	0.000	9.034	-3.820

Designing prediction model based on radial basis function (RBF) neural network

The prediction period of this research is 10 fiscal years from 2006 to 2015. Firstly, the data were divided into two sets; training and test. The contribution of learning set is 80% and that of trial set is 20%. Following the selection of variables using the metaheuristic algorithm Harmony Search, numbers are set between [1 and -1] according to the following formula;

$$f(x) = \frac{(e^x - e^{-x})}{e^x + e^{-x}} \quad (7)$$

Therefore, using the aforementioned statistical software, the data was automatically converted into numbers from 1 to -1. After this stage, weights were randomly assigned to data network and we proceeded with the network by transferring functions for each training (learning) and test sets. Using the back propagation of the error algorithm, the network with a number of neurons in hidden layer, error values were reduced to a minimum.

Criteria for the evaluation of prediction performance

To indicate how data links are learnt in a neural network, typically some criteria of performance are used. For prediction problems, the criteria are associated with errors between predicted outputs and real optimal outputs. In this research, the following criteria are used: mean squared error (MSE), normalized mean squared error (NMSE), the mean absolute percentage of error (MAPE), and the coefficient of determination (R^2).

Results of prediction by neural network

Hidden layers and nodes play an important role in the success of neural networks. Hidden nodes in hidden layers allow neural network to detect and identify data characteristics, so they do complex nonlinear mapping between input and output variables. In theory, neural networks can obtain desired precision with function approximation by using a sufficient number of hidden nodes (Lendass, 2000).

Table 5. Root means squared errors with a change in the number of hidden layer neuron

RMSE	Number of hidden layer neuron
0.0324	2
0.0314	4
0.0302	6
0.0323	8
0.0244	10
0.0226	15
0.0171	20
0.0169	25
0.0137	30
0.0158	35
0.0151	40
0.0153	45
0.0147	50

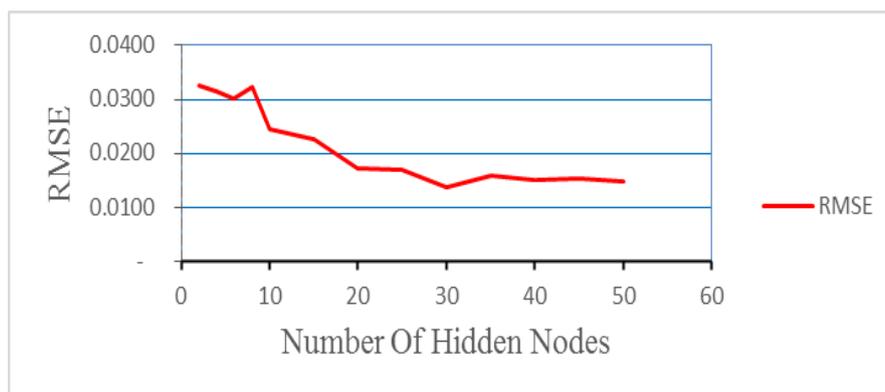


Fig. 4. Root means squared errors of the network based on different hidden layers

Different layers were tested for the determination of a suitable topology of a neural network. By changing the number of layers and the number of hidden layer neurons, the main model for prediction was selected. According to the table and the above table, the number of nodes that reduce network errors optimally is 30 hidden nodes.

By applying network inputs, the back propagation of error calculation is performed in the first place so that the output of neural network model is obtained. In what follows, the output error and the optimal level are calculated and distributed among existing layers on the basis of back propagation relationships, and then the weight matrix is corrected. The number of iteration is on average 870 for each firm in this method. For instance, the graph of network error correction rate is shown in Fig. 4 for average firms. The level of network error in each iteration is given by MLP neural network in order to aid the design in changing topology.

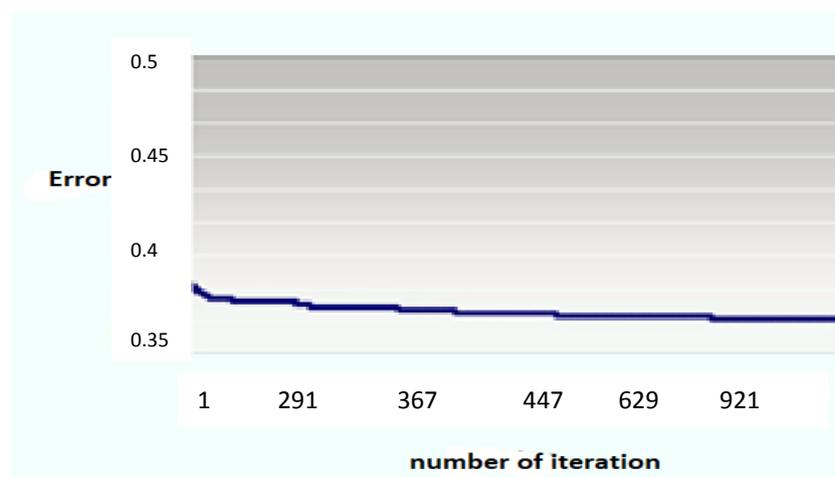


Fig. 5. Network error in each iteration of neural network

As can be seen, with an increase in the number of iterations, the rate of error correction declines and there would be almost no correction at final iterations. The final model for the results of the evaluation of neural network prediction based on the data of the balanced search for a number of sample firms is given in table 6. In

Fig. 3, real and predicted values are presented. It is observed that the neural network model optimized by balance search method of its input data according to tables 6 and 7 can on average predict 96% of real data. According to Table 7, RMSE is 27.94, MAE is 256.28, and R^2 is %96.5. Thus, it can be concluded that the neural network optimized by Harmony Search method of its input variables presents a desirable level of price-to-stock ratio prediction.

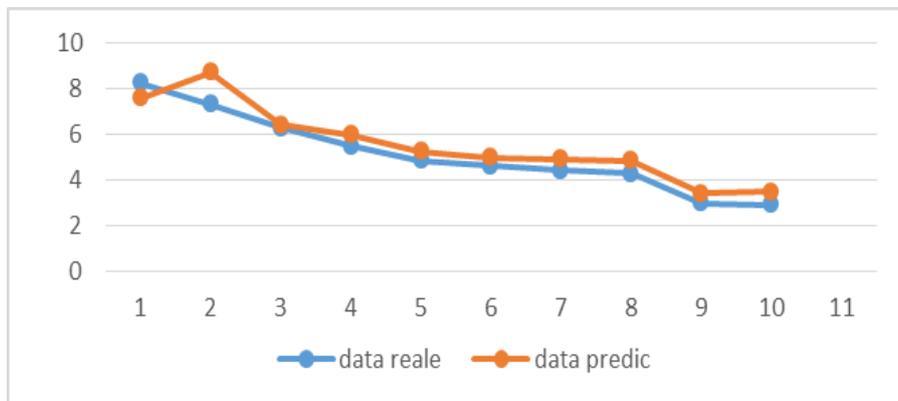


Fig. 6. Predicted values and real data

Table 6. Values of evaluation of neural network performance by using Harmony Search method for 8 select firms

R^2	MAPE	NMSE	MSE	Company	MODEL
0.97352	0.000244	0.073993	0.003221	Iran Transfer	Artificial neural network Harmony Search method
0.93244	0.004215	0.035535	0.00148	Iran Khodro	
0.95221	0.002942	0.046632	0.02193	Iran Khodro Diesel	
0.96114	0.000942	0.039825	0.01847	Iran Daroo	
0.98722	0.005991	0.030995	0.08224	Absal	
0.93860	0.000414	0.06332	0.04471	Bahman Group	
0.98932	0.004592	0.09332	0.015445	Saipa	
0.97878	0.006922	0.09124	0.03461	Behran Oil	

Table 7. Values of the evaluation of neural network performance by using Harmony Search method concerning different values of error

Error performance	Average price-to-earnings ratio for study firms
RMSE	274.9723
NMSE	0.036588
MAE	256.28543
Min Abs Error	13.29843
Max Abs Error	739.23882
R ²	0.96502

Discussion and Conclusion

In this research, the metaheuristic algorithm Harmony Search (HS) and neural network were used to design and explain P/E ratio prediction mode, increase the effectiveness, and reduce the costs and time. The results indicated that explanation and presentation of the prediction model of this critical ratio in shareholders' and investors' decision-making are more precise by far than the previous models and algorithms due to the high prediction power and the integration of the metaheuristic algorithm Harmony Search into neural network. Test statistics were designed and estimated for prediction, and the efficiency of their performance was compared using some criteria including root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage of error (MAPE). In the end, the neural network with three layers (input layer 10 nodes, middle layer 30 nodes, and output layer 1 node) was presented as the best model of neural network optimized by HS algorithm for prediction of firm's price-to-earnings ratio by means of BP training algorithm and Sigmoid transfer function with an average iteration of 870. Therefore, the research hypothesis is confirmed. The hypothesis suggests the possibility of using the metaheuristic algorithm Harmony Search for predicting P/E ratio by neural network. In this study, the data of a ten-year time span from 2006 to 2015 were used. It should be noted that the best model is the one with high accuracy in prediction. As a matter of fact, the closer to reality the estimation of a model is, the less errors it has in prediction. Thus, the criterion mean squared error was used, which is an acceptable criterion according to researchers.

Expressing research constraints precludes misconceptions and improper judgments. The most important limitations that existed in the course of this research are as follows:

1. Lack of access to reliable audited midterm data of listed companies in Tehran Stock Exchange. In case of access to these data, it would be possible to predict price per dividend ratio in shorter periods.

2. There was little research on the use of new meta-heuristic models such as harmony search of the literature, and hence the analyses indicating the use of this model that confronted prejudices.

3. In research projects with a long time span, e.g. a 10-year period, macroeconomic variables and even political variables of state changes affect stock performance and ratios coming from them. This was the case with the present study.

4. With the statistical population being limited to the companies listed in the Tehran Stock Exchange and their fiscal year ending by March 20, generalizing the results to other firms should be taken with caution.

5. Similarly, due to the limited time period of the research, generalizing its results to time spans before and after this research should be taken with caution.

6. Another feature of the harmony search algorithm is that it detects solution intervals with better performance domain in the most convenient time. This feature gets into trouble if the problem in question has a local optimum, and it stops at the local optimality and fails to reach the global optimum. The reason for this is the inefficiency of the algorithm in implementing local search for discrete optimization issues.

As can be seen, the results of this study are in line with those of Janeski and kalajdziski (2010), Budhani et al (2012). These studies separately investigated the precision of neural networks and the different types of prediction with bird flight algorithm, bee nest, econometrics, support vector machine, etc. The results indicated higher accuracy of combining neural network with new algorithms compared to other prediction methods. As this research utilized fundamental analysis in order to get a better understanding of the stock market behavior, it is suggested that for future studies, in an

attempt to get a better and stricter understanding of the stock price behavior, a combination of fundamental and technical analyses and intelligent algorithms such as Cuckoo's algorithms, bird algorithm and bacteria growth algorithm be designed in order to forecast P/E ratio and compare their performance with Harmony Search neural network, as well as the hybridization of Harmony Search algorithm with other intelligent algorithms and providing a combined algorithm for the prediction of price-to-earnings ratio be tested particularly in different industries, which can provide us with guidelines on the situation and differences of determinants to P/E prediction.

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