



Stock Price Analysis Using Machine Learning Method (Non-Sensory-Parametric Backup Regression Algorithm in Linear and Nonlinear Mode)

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ABSTRACT

The most common starting point for investors when buying a stock is to look at the trend of price changes. In recent years, different models have been used to predict stock prices by researchers, and since artificial intelligence techniques, including neural networks, genetic algorithms and fuzzy logic, have achieved successful results in solving complex problems; in this regard, more exploitation are. In this research, the prediction of stock prices of companies accepted in the Tehran Stock Exchange using artificial intelligence algorithm (non-sensory-parametric support vector regression algorithm in linear and nonlinear mode) has been investigated. The results of the research show that the PINSVR algorithm in nonlinear mode has been able to predict the stock price over the years, rather than linear mode.

1 Introduction

Stock price prediction is one of the most important tools for investing. It requires obtaining the right information from the stock market, changes in stock prices, and factors affecting it. The identification of influential factors and their impact on the stock market by experts requires strong technical knowledge and analysis that is not easily possible. Therefore, stock price prediction is a process over time (time series) due to the lack of knowledge of all factors and the extent to which they are affected by traditional methods with error, so stock price prediction is an important factor in which the investor. There is a need for powerful and reliable tools to predict stock prices. Since the stock market has a non-linear and chaotic system that is influenced by the political, economic, and behavioral conditions of investors, there are so many ways to advance. Stock price prediction has been used [24]. Stock price prediction is considered as one of the most challenging time series forecasting applications, although many empirical research deals with issues of stock price prediction, but the most empirical findings have been attributed to the development of financial markets. Stock price prediction as a challenging issue is the process of predicting time series, because the stock market is dynamically, nonlinear, complex, nonparametric and disorderly. In addition, stock prices are affected by a large number of macroeconomic factors, such as

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political events, inflation rates, general economic conditions, investor expectations and behavior, as well as financial variables such as transaction volumes, E/P ratios, and etc on stock prices of each Companies have a lot of influence and, in fact, direct the behavior of investors. Neural networks are more suitable for solving complex and nonlinear problems than timelines, although they have their own problems; for example, they are limited in learning because the stock price data has a significant difference and complex dimensions, and therefore It is very difficult to predict the price of a stock of labor [15]. Financial markets have an important role in the economy of every country and are effective factors in economic growth. The stock market is also one of these markets, which leads funds toward investment opportunities affect a large part of the economy in the world and cause a great deal of concern for the governments [21]. The achievement of long-term and continuous economic growth requires the equipping and optimal allocation of resources at the national economy level, and this is not easily possible without the help of financial markets, especially the extensive and efficient capital market. Investing in stocks listed on the stock exchange is one of the lucrative options in the capital market. However, the evaluation and forecasting of stocks or any other securities requires a historic trend and specialist expertise.

Different theories have been proposed regarding the valuation and prediction of stock prices in organized markets. In the early 20th century, a group of experienced experts in valuing securities believed firmly that it was possible to provide an image for predicting future stock prices by studying and analyzing the historical trend of stock price changes. More scientific studies, focusing on the precise identification of stock price behavior, have led to a tendency toward stock price valuation models. At first, the theory of random steps was introduced as a starting point in determining the behavior of stock prices. Then, attention was paid to the characteristics and structure of the capital market, which resulted in these studies and studies leading to an efficient capital market hypothesis. This hypothesis was considered by the scientific gatherings due to its specific composition. In the efficient capital market, stock prices are believed to reflect the current information about that share, and stock price changes do not have a specific and predictable pattern. Stock price prediction has always been a challenging issue for researchers [7]. The arguments raised until the 1980s clearly determined the behavior of stock prices in the market until the New York Stock Exchange developments in 1987, questioned the validity of the market capitalization assumptions and models such as the randomness of prices. In the 1990s and beyond, more attention was paid by experts to a turbulent behavior along with discipline and attempts to design nonlinear models in order to predict stock prices were of increasing importance [17].

2 Theoretical Foundations and Research Background

Stock price prediction is not an easy task because many market agents interfere in its determination, all of which can not be simply explained in the technical analysis (only historical data relating to the movement of prices and stock volumes to predict the future price movement of the study. Therefore, it has been proved that the use of more sophisticated computing tools and algorithms, such as artificial neural networks, of modeling nonlinear processes that result in the price and trend of stocks, the responses They are better off than statistical methods [20]. In a general classification, all of these methods can be found in one of the groups: fundamental analysis, technical analysis, time series prediction, and machine learning methods. The fundamental analysis attempts to predict stock prices by examining the company's data and the market in which it operates. Technical analysis

believes that the past always repeats itself, then identifies the patterns in the past data to predict the future. In prediction through time series, through the identification of relationships between independent variables and dependent on future predictions.

Machine learning methods try to use a series of special algorithms to discover hidden patterns between data. If the number of independent and dependent variables is high and there is no linear relationship between them, this method is the best option for prediction. In order to implement machine learning techniques, several methods such as artificial neural network, decision tree, clustering and classification Available. Therefore, it has been proved that using more sophisticated computing tools and algorithms, such as artificial neural networks, to model nonlinear processes that result in price and trend of stocks, provide better responses to statistical methods [20]. The use of intelligent techniques such as artificial neural networks, genetic algorithms, evolutionary strategy algorithm, particle pool optimization algorithm, rice paddy rice algorithm, ant colony optimization, honey bee colony and Golestan firefighting algorithm, predict these systems based on Experiences are considered as a series of times of this variable, which gives rise to the effective factors and relationships in the formation of a variable in its own values, so that its predecessor variables can be used as the most important source for explaining the changes and only predicts By studying the trends of these changes Cup Bayat and Beriberi [5]. The existence of sufficient market information and its timely and quick reflection on the price of securities is closely related to market efficiency. In the efficient market, information that is being distributed on the market quickly impacts prices. In such a market, the price of securities is close to its intrinsic value. In other words, the important feature of the efficient market is that the market price is a good indicator of the true value of the securities; therefore, the market is an efficient market, in which the price of securities, such as the price of ordinary shares, reflects all the information available on the market. The efficient market should be sensitive to new information. Influence of information on prices is the core of the market. This means that, as new information becomes available, immediate responses will arise, and thus prices will change.

In the financial literature, research on how stock prices react to market-based information and company specific information has become so important. In addition to the "direction" and "the rate of stock price change," another dimension in the market efficiency hypothesis has been formed that is the price adjustment rate to the reflection of new information [28]. The ideas posed by the 1980s were a good determinant of stock market behavior until New York Stock Exchange developments in 1987 seriously questioned the validity of capital market assumptions. In the 1990s and beyond, more attention was paid by specialists to a poignant behavior accompanied by discipline, and attempts were made to design nonlinear models to predict stock prices. Many recent studies have shown that the stock market is in fact a nonlinear and chaotic system which is dependent on political, economic, and psychological factors [9]. In order to overcome the limitations of traditional analysis techniques in predicting nonlinear patterns, in the past two decades, experts have been using intelligent techniques, especially artificial neural networks and genetic algorithms, to improve Stock price forecast [26]. How the investors react to the received information plays a crucial role in determining the return of stock exchange market. Supply and demand based upon incorrect decisions lead to the price deviation of inherent values[13-14]. Stock market is affected by news and information. If the stock market is not efficient, the reaction of stock price to news and information will place the stock market in overreaction and underreaction states [23].

Using statistical tests and reviewing trends and relationships between the variables, planning can be done to invest in it and its performance or inefficiency can be tested [1]. In Iran, the development of the Tehran Stock Exchange has been set up with the aim of mobilizing and equipping private savings toward generation and attraction of investors' public participation. One of the important issues in the stock market is stock prices as a signal in directing the volume of liquidity and effective allocation of capital that, if matched to the inherent value of the stock, becomes a powerful tool in the efficient allocation of resources, the changes in the price of stock is related to the systematic changes in the company's fundamental values and the investor's irrational behavior has no effect on stock returns[25]. Taghizadeh and Nazemi are analyzing the stock price network in the period of 2011-2012. Based on the type of data collected and analyzed, research is a bit of network analysis.

The research findings indicate that at the levels of correlation of 75% and 80% Iranian drug companies and pharmaceutical companies produce the drug with the highest degree of the role of the center of the network of solidarity stock prices and at 95%, Iran Pharmaceuticals are the only pharmaceutical companies to produce pharmaceuticals and Drug Razak is associated with pharmaceutical investment, and the rest of the companies are isolated at this level. In fact, the results of the review of the stock price network at the correlated levels (from 75% to 95%) indicate that the network in question does not have high density and concentration and increases with the increase of the grid parity correlation, increasing the disturbance of concern. For investors looking to reduce their portfolio risk, the growth of disorder increases the risk of their investment. Lakshmi et al in their article titled, "A new statistic for measuring the level of dependence toward the fluctuation of the stock price," in India, examined four indicators, including NIFTY, S & P500, FTSE100 and DAX, during the sample period from January 1996 to March 2015, and they showed that stock fluctuations are predictive of daily data [16]. Pakraei predicted the movement of stock movements using XCS-based genetic algorithm and reinforcement learning. In this research, a model is presented that uses XCS to predict the future stock market trend of one of the active companies in the Tehran Stock Exchange based on historical data and the use of various technical profiles. Then, the prediction accuracy of the proposed model is compared with that of stroke model. The results indicate that the proposed model has a higher predictive accuracy compared to the stroke model [22].

Ashraf et al in an examination of the comparative evidence of the relationship between stock prices and the value of accounting information based on IFRS in Germany and the United Kingdom, stated that there was a long-term relationship between accounting variables and stock price changes in countries with common laws such as in the United Kingdom [3]. Fakhary and RezaeiPithenei analyzed the impact of the audit committee on the company's information environment. The company's information environment was measured by the variables of the company's size, institutional ownership, company growth opportunities, company life cycle, bid price range, shareholder, Profit prediction error, frequency of stock turnover, non-cash maturity and stock return volatility as a comprehensive index, and the impact of the audit committee on the corporate information environment over a period of 4 years before and after the approval of the internal control instructions. In 2012, it was tested during the years 2008 to 2015. The results of a survey of 41 companies that formed the Audit Committee after approval of the Internal Control Instructions in 2012, through panelized data, indicate that there is a positive and significant relationship between the existence

of the audit committee and the company's information environment. Moreover, with the establishment of the audit committee in companies, their information environment became clearer and the index increased [11].

Bartov et al investigated the behavior of investors in dealing with the reflection of profitability of unexpected items in the form of profit and loss statement. They showed that investors showed a reaction to disclosure of profit and loss of unexpected items. Therefore, the disclosure of unexpected items in the context of profit and loss statement is directly related to the price of the stock. Their findings are consistent with the behavioral stability hypothesis[8]. Islami et al studied the effect of internal factors on changes in stock prices of investment companies listed in Tehran Stock Exchange. The statistical population of the study includes all investment companies in the financial intermediation industry and related activities during the period of 2008 to 2014. The three variables of earnings per share, cash dividends per share, and the ratio of price to earnings, the liquidity ratio affect supply and demand, and ultimately stock prices more than other factors [12]. According to the mentioned theoretical principles and the aim of the research, the following hypotheses are developed.

- 1) Artificial intelligence algorithm Non-parallel non-parallel support vector regression in nonlinear mode has the higher ability to predict this year's stock price than linear mode.
- 2) Artificial intelligence algorithm Nonlinear non-parallel non-sensory-parametric non-parallel vector support regression has the ability to predict future stock prices in a linear fashion.
- 3) Artificial intelligence algorithm. Non-parallel non-parasitic-parametric non-paramterical support regression. Non-parallel non-parallel nonparallel support vector regression in nonlinear state has higher ability to predict stock prices for the next two years than linear mode.

3 Research Methodology

In today's world, there are many issues that can be addressed by algorithms and appropriate solutions for them. One of the applications of algorithms in industry and commerce is that it is necessary to allocate rare resources with the most advantageous method, so that with limited resources we can achieve maximum and minimum profits.

3.1 Population and statistical sample of research

This research is applied based on the purpose and in terms of the type, is a field-library study using historical information as an after-event (using past information). The statistical population of this research includes all companies accepted in Tehran stock exchange which have the following conditions.

1. During the course of study, there should be no change in the financial period.
2. They should not be one of investment companies, financial intermediaries, banks, insurance and leasing.
3. Their considered data be available.

Finally, due to the limitations mentioned. 1170 year-company has been selected as a statistical population between 2011 and 2016, which, considering the availability of information, all companies have been considered as the statistical sample.

3.2 Research variables

Financial ratios are considered to be useful tools in accounting for financial statements of companies, which, by presenting the ratio of some important accounting items, obtain an understanding of important assets in the period between the results of operations and the financial position of a company. A variable is a concept that is assigned more than two or more values or numbers. In other words, the variable refers to features that can be viewed or measured. And replaced two or more values or numbers.

Table 1: The variables used in this research .

Operational definition	
Net profit margin	Return on Assets
Return on Equity	Earnings Per Share
Current ratio	Immediate ratio
Ratio of working capital	Financial leverage
Debt to equity ratio	Inventory turnover ratio
Fixed asset turnover ratio	Asset Turnover Ratio
Turnover of Receivable Accounts	Ratio of market value to book value of assets
Systematic Risk	Return on Equity
Unconditional conservatism	Conditional conservatism
Cash / asset ratio	Operating cash ratio
Ratio of Current Assets	Ratio of Current Debt to Equity
Long-term debt ratio	Size of the company
Dividend Profit Ratio	Tax avoidance
The price / profit ratio	
The dependent variable	
Stock price	Stock price information of the companies at the end of the fiscal year
Research period	2011- 2016 (6-year period)
Research design	Two-stage approach, 1- Variable selection test 2- Stock price forecast

4 Variable Selection

Feature Selection Method Based on Lars's Algorithm

Suppose we have sets of variables $n+1$ that are set up x_1, x_2, \dots, x_n, y . In the approximation of function 18 (regression 19), we seek a function (or model) that approximates the value of the dependent variable y as a linear function of $x_j, j = 1, \dots, n$ the independent variable. Vector $x \in R^n = (x_1, x_2, \dots, x_n)'$ is a vector of independent variables. The goal is to find f as to have $y = f(x)$. Suppose we know that $f(x)$ belongs to linear models, that is, $f(x) = \sum_{j=1}^n x_j \beta_j + p = \langle x, \beta \rangle + p$ in which

Efron, B., et al (2004) studied Least Angle Regression (LARS). The advantages of this algorithm are 1) we need only M steps that M is the number of independent variable, 2) Selecting a new variable dependent on the previous selected set of variables. The second advantage is the key advantage of this algorithm that leads to select independent variables dependent on each other [10]. Let's now summarize the LARS algorithm with respect to the correlation r1 between x and Y, and Rx correlation matrices of the variables is summarized as follows:

1. $A = \phi, \quad s_A = \phi$
2. $m = \arg \max |r_j|, \quad s_m = \text{sign}\{r_m\}, \quad r = s_m r_m$
3. $A \leftarrow A \cup \{m\}, \quad s_A \leftarrow s_A \cup \{s_m\}$
4. Calculate $a = [1'_A (D_A R_A D_A)^{-1} 1_A]^{\frac{1}{2}}$ where $D_A = \text{diag}(s_A), \quad R_A \subset R_X$
 Calculate $w_A = a (D_A R_A D_A)^{-1} 1_A$
 and for $j \in A^c : a_j = (D_A r_{jA})' w_A$

Which r_{jA} is a vector of correlation between X_j and active variables. (Note: When there is only one active variable:) $a = 1, \quad w = 1, \quad a_j = r_{jm}$

5. for $j \in A^c$ Calculate $\gamma_j^+ = \frac{r - r_j}{a - a_j}, \gamma_j^- = \frac{r + r_j}{a + a_j}$
 $\gamma_j = \min(\gamma_j^+, \gamma_j^-), \quad \gamma = \min(\gamma_j, j \in A^c)$

If m is the index of arg min, we have $Y = Y_m$.

if $\gamma_m = \gamma_m^+$ then $s_m = +1$ else $s_m = -1$

for $j \in A^c$ Modify $r \leftarrow r - \gamma a, \quad r_j \leftarrow r_j - \gamma a_j$

Repeat 3,4,5 steps

Table 2: Selected independent variables with weight (significance).

	Selected independent variables	Weight
X1	Earnings per share	5.277
X2	P to e ratio	3.953
X3	size of the company	130.347
X4	Inventory turnover ratio	8.331
X5	Stock returns	2.485

After selecting the independent variables of the problem, these independent variables were given to construct the model to the particle and chad motion algorithm. Subsequently, these algorithms were investigated. Mass particle swarm optimization algorithm. The PSO is of optimization algorithms that operate on the basis of random primary population generation. This algorithm is based on the simulation of the behavior of massive (group) bird flying or collective movement (grouping) of fish. Each member

in this group is defined by the vector of the velocity and position vector in the search space. In each time repetition, the new particle position is defined according to the vector of velocity and position vector in the search space. At each time interval, the new particle position is updated according to the current velocity vector, the best position found by that particle, and the best position found by the best particle in the group. This algorithm was initially defined for continuous parameters, but given the fact that in some applications we deal with discrete parameters, this algorithm is also expanded in a discrete state. The particle swarm optimization algorithm is introduced in an enhanced binary state with (BPSO). Early definitions of the PSO algorithm

Suppose we have a d-dimensional search space. i th particle in this d-dimensional space is described with the position vector X_i as follows:

$$X_i = (x_{i_1}, x_{i_2}, x_{i_3}, \dots, x_{i_d}) \quad (1)$$

The vector of velocity of i th particle is also determined by the vector V_i as follows:

$$V_i = (v_{i_1}, v_{i_2}, v_{i_3}, \dots, v_{i_d}) \quad (2)$$

We define the best position i th particle have found with $P(i.best)$:

$$P_{i.best} = (p_{i_1}, p_{i_2}, p_{i_3}, \dots, p_{i_d}) \quad (3)$$

The best position that the best particle has found in the whole particle is defined by $P_{g.best}$ as follows:

$$P_{g.best} = (p_{g_1}, p_{g_2}, p_{g_3}, \dots, p_{g_d}) \quad (4)$$

We use the following for updating the location of each particle:

$$V_i(t) = w * V_i(t-1) + c_1 * rand_1(P_{i.best} - X_i(t-1)) + c_2 * rand_2(P_{g.best} - X_i(t-1)) \quad (5)$$

$$X_i = X_i(t-1) + V_i(t)$$

Where w is the inertial mass index (motion in the same path), which indicates the effect of the velocity vector in the previous repetition on the velocity vector in the current repetition ($V_i(t+1)$). C_1 is the constant coefficient of training (moving in the direction of the best value of the particle being examined), c_2 is the constant coefficient of training (motion on the path of the best found particle in the total population), $rand_1$ and $rand_2$ are two random numbers with uniform distribution in the interval 0 to 1, $V_i(t-1)$ is the velocity vector in the repetition (t-1)th, $X_i(t-1)$ is the position vector in the repetition (t-1). To avoid excessive increase in the velocity of a particle moving from one location to another (the velocity divergence), we limit the velocity changes to the range V_{min} to V_{max} ; $V_{min} \leq V \leq V_{max}$ the upper and lower limit is determined by the type of problem.

Non-Paradox Non Parallel Support Vector Regression (PINSVR)

In this section, the PINSVR model is provided. The purpose of the PINSVR is to evaluate the regression model through the automatic matching of the non-sensory-parametric area of an arbitrary shape with the minimum size, which includes the data to store the data size and border information with a higher accuracy.

LinePINSVR

Suppose that the set of observations (company-year) is N together with the input vector (independent

variables) x , all of which are years represented by an X matrix, so that the n th row is represented by x_n^T and represents the independent variables of the company n and $n = 1, 2, \dots, N$, and y denotes the dependent variable, the stock price. The PINSVR algorithm seeks to find non-parallel proximal linear functions $f_1(x)$ and $f_2(x)$ simultaneously, as well as two non-parallel linear proximal linear functions $g_1(x)$ and $g_2(x)$. These functions are shown below.

$$f_1(x) = w_1^T x + b_1, f_2(x) = w_2^T x + b_2 \tag{1}$$

$$g_1(x) = w_3^T x + b_3, g_2(x) = w_4^T x + b_4 \tag{2}$$

Where $g_1(x) \geq 0$ and $g_2(x) \geq 0$. The two non-sensory-damaging functions of the arbitrary 22 are defined as follows:

$$L^{g_1}(x, y, f_1) = \sum_{i=1}^m \max\{0, -(y_i - f_1(x_i) + g_1(x_i))\}$$

$$L^{g_2}(x, y, f_2) = \sum_{i=1}^m \max\{0, -(f_2(x_i) - y_i + g_2(x_i))\}$$

Therefore, the experimental risk in this algorithm is defined as follows:

$$R_{emp}^{g_1}[f_1] = \sum_{i=1}^m \max\{0, (y_i - f_1(x_i))^2\} + c_1 \sum_{i=1}^m \max\{0, -(y_i - f_1(x_i) + g_1(x_i))\} \tag{3}$$

$$R_{emp}^{g_2}[f_2] = \sum_{i=1}^m \max\{0, (f_2(x_i) - y_i)^2\} + c_2 \sum_{i=1}^m \max\{0, -(f_2(x_i) - y_i + g_2(x_i))\} \tag{4}$$

Where $c_1 > 0$ and $c_2 > 0$ are its parameters. Primary optimization problems for PINSVR are defined as follows:

$$\begin{aligned} \min_{w_1, w_3, b_1, b_3, \xi} & \frac{1}{2} c_3 (w_1^T w_1 + b_1^2 + w_3^T w_3 + b_3^2) + \frac{1}{2} \xi^{*T} \xi^* + c_1 e^T \xi \\ \text{s. t.} & \begin{cases} Y - (Aw_1 + eb_1) = \xi^* \\ Aw_3 + eb_3 \geq 0 \\ Y - (Aw_1 + eb_1) \geq -(Aw_3 + eb_3) - \xi, \xi \geq 0 \end{cases} \end{aligned} \tag{5}$$

$$\begin{aligned} \min_{w_2, w_4, b_2, b_4, \eta} & \frac{1}{2} c_4 (w_2^T w_2 + b_2^2 + w_4^T w_4 + b_4^2) + \frac{1}{2} \eta^{*T} \eta^* + c_2 e^T \eta \\ \text{s. t.} & \begin{cases} (Aw_2 + eb_2) - Y = \eta^* \\ Aw_4 + eb_4 \geq 0 \\ (Aw_2 + eb_2) - Y \geq -(Aw_4 + eb_4) - \eta, \eta \geq 0 \end{cases} \end{aligned} \tag{6}$$

Where c_1, c_2, c_3 and c_4 are input parameters of the problem. Now geometric explanation of the optimization problem, a simple two-dimensional example of the implementation of the PINSVR algorithm to the loss function is shown in Fig. 3. The first term in the objective function (5) is to minimize the expression $\frac{1}{2} c_3 (w_1^T w_1 + b_1^2 + w_3^T w_3 + b_3^2)$ that controls the complexity of the

model $f_1(x)$ and $g_1(x)$. In other words, $f_1(x)$ adheres to the data as much as possible, and g_1 is the downstream recorder of the data structure. In addition, the structural risk in relation (5) is minimized due to my setting of $2\frac{1}{2}c_3(w_1^T w_1 + b_1^2)$.

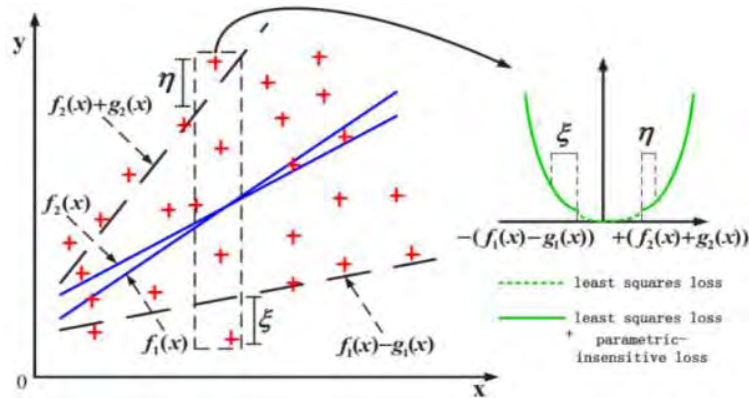


Fig. 3: Two-dimensional geometric interpretation and target function settings of the PINSVR algorithm

The second term in the objective function (5) according to $Y - (Aw_1 + eb_1) = \xi^*$ denotes the squares squared error function error 24 between the value of the decision function $f_1(x) = w_1^T x + b_1$ and the dependent variable for the sample X is the label labeled with Y ; therefore, minimizing this term means a better approximation of the dependent variable by the PINSVR. The first implies that the value of $f_1(x) \geq 0$. The goal of the second unequal constraint of the objective function (23-3) is that the two functions $f_1(x)$ and $g_1(x)$ are at a minimal distance, so that the tutorials must be greater than $f_1(x)$, at least $g_1(x)$. The auxiliary vector is 5ξ to measure the error whenever the samples reject the line $g(x)$. The third term of the objective function minimizes the sum of the ξ variables, that is, the algorithm tries to keep the samples from the line $g_1(x)$ as far as possible and all sides of this line. For the optimization problem (6), there is a similar explanation. Using the Lagrange function and examining the conditions for the KKT dual function, two optimization problems (5) and (6) are obtained as a dual problem.

$$\min_{\alpha, \beta} \frac{1}{2c_3} \alpha^T G G^T \alpha + \frac{1}{2} \beta^T \left(G(G^T G + c_3 I_1)^{-1} G^T + \frac{1}{c_3} G^T G \right) \beta + \frac{1}{c_3} \alpha^T G G^T \beta - Y^T (G(G^T G + c_3 I_1)^{-1} G^T - I_2) \beta$$

$$s. t. \begin{cases} \alpha \geq 0 \\ 0 \leq \beta \leq c_1 e \end{cases} \quad (7)$$

$$\min_{\alpha^*, \beta^*} \frac{1}{2c_4} \alpha^{*T} G G^T \alpha^* + \frac{1}{2} \beta^{*T} \left(G(G^T G + c_4 I_1)^{-1} G^T + \frac{1}{c_4} G^T G \right) \beta^* + \frac{1}{c_4} \alpha^{*T} G G^T \beta^* - Y^T (G(G^T G + c_4 I_1)^{-1} G^T - I_2) \beta^*$$

$$s. t. \begin{cases} \alpha^* \geq 0 \\ 0 \leq \beta^* \leq c_2 e \end{cases} \quad (8)$$

Where $G = [A \quad e]$. From the solution of equation (7), the Lagrange coefficients α and β are obtained, and it is obtained by putting it in the following relationships with the values of the parameters $f_1(x)$ and $g_1(x)$:

$$u_1 = (G^T G + c_3 I_1)^{-1} G^T (Y - \beta) \tag{9}$$

$$u_3 = \frac{1}{c_3} G^T (\alpha + \beta) \tag{10}$$

Where $u_1 = [w_1^T b_1^T]^T$ and $u_3 = [w_3^T b_3^T]^T$. From the optimization solution (8), the Lagrangian coefficients α^* and β^* are obtained, and it is obtained by putting it in the following relations for the parameters of the line $f_2(x)$ and $g_2(x)$:

$$u_2 = (G^T G + c_4 I_1)^{-1} G^T (Y - \beta^*) \tag{11}$$

$$u_4 = \frac{1}{c_4} G^T (\alpha^* + \beta^*) \tag{12}$$

Now the linear decision function of this algorithm is obtained as follows:

$$f(x) = \frac{1}{2} (f_1(x) + f_2(x)) = \frac{1}{2} (w_1 + w_2)^T x + \frac{1}{2} (b_1 + b_2) \tag{13}$$

The upper and lower bounds of the regression model are calculated as follows:

$$f_1(x) - g_1(x) = (w_1 - w_3)^T x + b_1 - b_3 \tag{14}$$

$$f_2(x) + g_2(x) = (w_2 + w_4)^T x + b_2 + b_4 \tag{15}$$

PINSVR Cornell

In this section, the linear PINSVR is extended to nonlinear mode using kernel tricks. The input data is mapped to a high-dimensional space using nonlinear kernel functions. In the characteristic space, the linear regression function corresponds to the nonlinear regression function in the input space, as shown in Figure 4 of this topic. Similar to the linear mode, nonlinear nonlinear proximal functions $f_1(x)$ and $f_2(x)$ and two nonlinear nonlinear proximal nonlinear functions $g_1(x)$ and $g_2(x)$ are considered as follows.

$$f_1(x) = k(x^T, A^T) w_1 + b_1, f_2(x) = k(x^T, A^T) w_2 + b_2 \tag{16}$$

$$g_1(x) = k(x^T, A^T) w_3 + b_3, g_2(x) = k(x^T, A^T) w_4 + b_4 \tag{17}$$

Where k is the kernel function and $g_1(x) \geq 0$ and $g_2(x) \geq 0$. The initial problem of nonlinear PINSVR is defined as follows:

$$\begin{aligned} \min_{w_1, w_3, b_1, b_3, \xi} & \frac{1}{2} c_3 (w_1^T w_1 + b_1^2 + w_3^T w_3 + b_3^2) + \frac{1}{2} \xi^{*T} \xi^* + c_1 e^T \xi \\ \text{s. t. } & \begin{cases} Y - (k(A, A^T) w_1 + e b_1) = \xi^* \\ k(A, A^T) w_3 + e b_3 \geq 0 \\ Y - (k(A, A^T) w_1 + e b_1) \geq -(k(A, A^T) w_3 + e b_3) - \xi, \xi \geq 0 \end{cases} \end{aligned} \tag{18}$$

$$\min_{w_2, w_4, b_2, b_4, \eta} \frac{1}{2} c_4 (w_2^T w_2 + b_2^2 + w_4^T w_4 + b_4^2) + \frac{1}{2} \eta^{*T} \eta^* + c_2 e^T \eta$$

$$\text{s. t. } \begin{cases} (k(A, A^T)w_2 + eb_2) - Y = \eta^* \\ k(A, A^T)w_4 + eb_4 \geq 0 \\ (k(A, A^T)w_2 + eb_2) - Y \geq -(k(A, A^T)w_4 + eb_4) - \eta, \eta \geq 0 \end{cases} \quad (19)$$

Where c_1, c_2, c_3 and c_4 are input parameters of the problem. Using the Lagrange function and examining the KKT conditions of the dual function, two optimization problems (18) and (19) are obtained as a dual problem (Yang et al., 2014)

$$\min_{\alpha, \beta} \frac{1}{2c_3} \alpha^T H H^T \alpha + \frac{1}{2} \beta^T \left(H(H^T H + c_3 I_1)^{-1} H^T + \frac{1}{c_3} H^T H \right) \beta + \frac{1}{c_3} \alpha^T H H^T \beta$$

$$- Y^T (H(H^T H + c_3 I_1)^{-1} H^T - I_2) \beta$$

$$\text{s. t. } \begin{cases} \alpha \geq 0 \\ 0 \leq \beta \leq c_1 e \end{cases} \quad (20)$$

$$\min_{\alpha^*, \beta^*} \frac{1}{2c_4} \alpha^{*T} H H^T \alpha^* + \frac{1}{2} \beta^{*T} \left(H(H^T H + c_4 I_1)^{-1} H^T + \frac{1}{c_4} H^T H \right) \beta^* + \frac{1}{c_4} \alpha^{*T} H H^T \beta^*$$

$$- Y^T (H(H^T H + c_4 I_1)^{-1} H^T - I_2) \beta^*$$

$$\text{s. t. } \begin{cases} \alpha^* \geq 0 \\ 0 \leq \beta^* \leq c_2 e \end{cases} \quad (21)$$

Where $H = [k(A, A^T) \quad e]$. From the solution of (20), the Lagrange coefficients α and β are obtained, and it is obtained by placing it in the following relations with the values of the parameters $f_1(x)$ and $g_1(x)$:

$$u_1 = (H^T H + c_3 I_1)^{-1} H^T (Y - \beta) \quad (22)$$

$$u_3 = \frac{1}{c_3} H^T (\alpha + \beta) \quad (23)$$

Where $u_1 = [w_1^T b_1^T]^T$ and $u_3 = [w_3^T b_3^T]^T$. From the solution to the optimization (21), the stabilization (α^* and β^* is achieved), and from its placement in the following relationships, the values of the parameters $f_2(x)$ and $g_2(x)$ are obtained:

$$u_2 = (H^T H + c_4 I_1)^{-1} H^T (Y - \beta^*) \quad (24)$$

$$u_4 = \frac{1}{c_4} H^T (\alpha^* + \beta^*) \quad (25)$$

Now the linear decision function of this algorithm is obtained as follows:

$$f(x) = \frac{1}{2} (f_1(x) + f_2(x)) = \frac{1}{2} (w_1 + w_2)^T k(A, x) + \frac{1}{2} (b_1 + b_2) \quad (26)$$

The upper and lower bounds of the regression model are calculated as follows:

$$f_1(x) - g_1(x) = (w_1 - w_3)^T k(A, x) + b_1 - b_3 \quad (27)$$

$$f_2(x) + g_2(x) = (w_2 + w_4)^T k(A, x) + b_2 + b_4 \tag{28}$$

Table 3: Average SMAPE error criterion for assessing the training of algorithms every three years

error	Current year		Next year		The next two years	
SMAPE	Linear	NonLinear	Linear	NonLinear	Linear	NonLinear
Fold						
1	0.21	0.9	0.27	0.20	0.30	0.26
2	0.21	0.9	0.26	0.20	0.30	0.26
3	0.21	0.9	0.27	0.21	0.30	0.26
4	0.22	0.9	0.27	0.21	0.30	0.26
5	0.22	0.9	0.27	0.21	0.30	0.25
6	0.21	0.9	0.27	0.21	0.31	0.24
7	0.22	0.9	0.27	0.21	0.30	0.26
8	0.21	0.9	0.27	0.21	0.31	0.26
9	0.21	0.9	0.27	0.20	0.30	0.26
10	0.22	0.8	0.27	0.20	0.30	0.26
Mean	0.21	0.9	0.27	0.21	0.30	0.26

Table 4: Average SMAPE error rate for evaluating performance with test data every three years

error	Current year		Next year		The next two years	
SMAPE	Linear	NonLinear	Linear	NonLinear	Linear	NonLinear
Fold						
1	0.22	0.12	0.26	0.25	0.29	0.32
2	0.22	0.11	0.32	0.30	0.29	0.31
3	0.24	0.13	0.26	0.22	0.31	0.36
4	0.20	0.13	0.22	0.22	0.29	0.29
5	0.21	0.13	0.27	0.24	0.28	0.32
6	0.22	0.10	0.26	0.25	0.39	0.40
7	0.18	0.12	0.27	0.25	0.29	0.32
8	0.24	0.14	0.27	0.28	0.25	0.27
9	0.22	0.13	0.29	0.29	0.32	0.29
10	0.21	0.16	0.27	0.27	0.31	0.31
Mean	0.22	0.13	0.27	0.27	0.30	0.32

But what we need to worry about is the occurrence of a phenomenon called over-fit. Therefore, in order to review the generality of the models presented, the error rate to predict the dependent variable of the stock price in each three years for the company-years of testing (the company-years that were discarded by the 10-fold cross-validation method and the algorithm They have not seen them so far). For each error criterion, 10 errors, each reported by the 10-Fold Cross-Validation method, show that these errors, along with their mean for every three years, are shown in Table 3. As before, it is concluded that the achieved models are generic, that is to say, for companies that have not seen it all, well, and that the problem of overlapping has not happened, as the difference between the criteria of the error of the training and evaluation data is negligible. In addition, the PINSVR linear model has a relatively large error and can not properly predict the dependent variable of the stock price in comparison with the other two algorithms [27]. In order to evaluate linear and nonlinear regression models, the mean absolute

magnitude of symmetric error (SMAPE) has been used.

$$SMAPE = \frac{1}{n} \frac{\sum_{i=1}^n |d_i - y_i|}{\sum_{i=1}^n (d_i + y_i)}$$

As seen above, the nonlinear PINSVR algorithm with a percentage error of 0.13 SMAPE for this year, 0.25 for the year to come, and 0.32 for the next two years, have the best prediction for stock price evaluation. These results indicate that the PINSVR algorithm in nonlinear mode has been able to predict stock prices over the years, rather than linear.

5 Results and Discussion

Stock price prediction is considered as one of the most challenging time series forecasting applications, although many empirical research deals with issues of stock price prediction, but the most empirical findings have been attributed to the development of financial markets. Stock price prediction as a challenging issue is the process of predicting time series, because the stock market is dynamically, nonlinear, complex, nonparametric and disorderly. In addition, stock prices are affected by a large number of macroeconomic factors, such as political events, inflation rates, general economic conditions, investor expectations and behavior, as well as financial variables such as transaction volumes, E / P ratios, and ... on stock prices of each Companies have a lot of influence and, in fact, direct the behavior of investors. Neural networks are more suitable for solving complex and nonlinear problems than timelines, although they have their own problems; for example, they are limited in learning because the stock price data has a significant difference and complex dimensions, and therefore It is very difficult to predict the price of a stock of labor [14]. Artificial intelligence algorithms may be the best way to predict stock markets, but they do not come to a standstill.

These algorithms are ideal tools that, in addition to exploiting statistics, also consider mental aspects; therefore, it is possible to predict the stock price with this algorithm. The results of this research are the most conducted research in this field, namely, stock price prediction with The algorithm is intelligent; therefore, the main hypothesis of this research is confirmed, and AI algorithm is an efficient way to predict stock prices, and it is suggested to capital market analysts that the power of the PINSVR algorithm in nonlinear mode is better than predicting the linear price of stock. And with the Peugeot of Rosandel and Amir Manners review and compare data mining techniques to predict stock prices universe setting Qrardadnd test and Byghasadeh Abbasi et al in their review of stock price prediction using the genetic algorithm, states that investing in stock exchanges on stock exchanges is one of the most lucrative options in the capital market. The stock market has a nonlinear system of chaos that is affected by political, economic, and economic conditions, and nonlinear systems such as genetic algorithms can be used to predict stock prices. Similar results have been achieved. In the case of other research variables studied by Codiswako in his research, the effect of specific factors on stock prices among companies admitted to the Columbia Stock Exchange, the results of which indicate a positive and significant relationship between the specific factors of the company, the cash flow of each share, Earnings per share and the value of the asset of each share with the stock price. The results are the same.

References

- [1] Alijani, M., Banimahd, B., Madanchi, M., *Study and Research on the Six-Year Process of Bitcoin Price and Return*, Advances in Mathematical Finance and Applications, 2019, 4(1), P. 45-54.

Doi: 10.22034/amfa.2019.577434.1126

- [2] Andrea ,B., Matteo, M., *The impacts of oil price shocks on stock market volatility: Evidence from the G7 countries*, Energy Policy, 2016, **98**(c), P.160-169. Doi: 10.1016/j.enpol.2016.08.020
- [3] Ashraf, E., Elbakrya, J., Nwachukwub, H., Abdouc, D., *Comparative evidence on the value relevance of IFRS-based accounting information in Germany and the UK*, Journal of International Accounting, Auditing and Taxation, 2016, **28**, P. 10–30. Doi:10.1016/j.intaccudtax.2016.12.002
- [4] BarzegariKhanagha, J., Jamali, Z., *Predicting Stock Returns with Financial Ratios; An Exploration in Recent Researches*, Journal of Accounting Research, 2016, **6**(2), P. 71-92, Doi: 10.22051/ijar.2016.2432.
- [5] Bayat, A., Bagheri, Z., *The Predication of Stock Price Using Firely Algorithm*, Financial Knowledge of Securities Analysis, 2017, **10**(35), P. 135-145.
- [6] Alimohamadi, A., Abbasimehr, M., Javaheri, A., *Prediction of Stock Return Using Financial Ratios: A Decision Tree Approach*, Financial Management Strategy, 2015, **3**(4), P.125-146. Doi:10.22051/jfm.2016.2349.
- [7] AhmadKhanBeygi, S., Abdolvand, N., *Stock Price Prediction Modeling Using Artificial Neural Network Approach and Imperialist Competitive Algorithm Based On Chaos Theory*, Financial Management Strategy, 2017, **5**(3), P. 27-73. Doi: 10.22051/jfm.2017.14635.1319.
- [8] Bartov, E., Partha ,M. *Does Income Statement Placement Matter to Investors? The Case of Gains/Losses from Early Debt Extinguishment Leonard N*, Stern School of Business, New York University, New York, 2012. Doi: 10.2308/1558-7967-89.6.i.
- [9] Chia, L., Yung, L., *A double-threshold GARCH model of stock market and currency shocks on stock returns*, Mathematics and Computers in Simulation, 2008, **79**(3) , P. 458-474. Doi: 10.1016/j.matcom.2008.01.048.
- [10] Dibachi, H., Behzadi, M.H., Izadikhah, M., *Stochastic Modified MAJ Model for Measuring the Efficiency and Ranking of DMUs*, Indian Journal of Science and Technology, 2015, **8** (8), P. 549–555, Doi: 10.17485/ijst/2015/v8iS8/71505
- [11] Fakhari, H., Rezaei Pitenoei Y., *Explaining a Model for Measuring Corporate Information Environment*. Quarterly financial accounting journal, 2017, **9**(33), P.121-147.
- [12] Islami, M., Abadi, H., Saeedi, P., and Khalilzadeh, S., *Investigating the Effect of Internal Factors on Stock Price Change in Investment Companies Accepted in Tehran Stock Exchange*, Accounting Research, 2017, **6**(4), P. 103-138, (in Persian). Doi: 10.22051/IJAR.2017.2080.
- [13] Izadikhah, M., *Using goal programming method to solve DEA problems with value judgments*, Yugoslav Journal of Operations Research, 2016, **24** (2), P. 267–282, Doi: 10.2298/YJOR121221015I
- [14] Khaleghi, P., Aghaei, M., Rezaei, F., *Saliency Theory and Pricing Stock of Corporates in Tehran Stock Exchange*. Advances in Mathematical Finance and Applications, 2018, **3**(4), P. 1-16. Doi: 10.22034/amfa.2019.577140.1120

- [15] KiyaniMavi, R., SayadiNik, K. *Using different learning algorithms in the stock price prediction by using neural networks*, Journal of Development & Evolution Mangement, 2015, P. 75-81.
- [16] Lakshmi, P.,Maheswaran, S., *A New Statistic to Capture the Level Dependence in Stock Price Volatility*. The Quarterly Review of Economics and Finance, 2017, P. 355-362. Doi: 10.1016/j.qref.2016.12.001
- [17] Monadjemi, S., Abzari, M., Rayati Shavazi, A., *Modeling of Stock Price Forecasting in Stock Exchange Market, using Fuzzy Neural Networks and Genetic Algorithms*, Journal of Quantitative Economics, 2009, **6**(22), P. 1-26. Doi: 10.22055/jqe.2009.10697.
- [18] Meshki, M., Elahi Rodposhti, S., *Accounting Conservatism and the Value of Cash Holdings*, Empirical Research in Accounting, 2014, **4**(1), P. 23-43. Doi: 10.22051/jera.2015.1882
- [19] Metghalchi, M., Linda, A., *History of share prices and market efficiency of the Madrid general stock index*, International Review of Financial Analysis, 2015, **40**, P. 178-184, Doi: 10.1016/j.irfa.2015.05.016
- [20] Naghdi, S., Arab MazarYazdi, M., *Forecasting EPS o with Hybrid Genetic algorithm, particle swarm optimization and Neural networks*, Journal of Accounting Knowledge, 2017, **8**(3), P. 7-34. Doi: 10.22103/jak.2017.7086.2051
- [21] Nguyen Ngoc Thanh, V., *Determinants of Stock Price Synchronicity evidence from HoChiMinh city stock exchange*. Doctoral dissertation, Vietnam, International University HCMC, 2013. Doi: 10.22161/ijaers.4.4.14
- [22] Pakraei, A., *Predict the trend of stock prices using XCS based on genetic algorithms and reinforcement learning*, Financial Knowledge of Securities Analysis, 2017, **10**(34), P. 39-54.
- [23] Parsa, B., Sarraf, F., *Financial Statement Comparability and the Expected Crash Risk of Stock Prices*, Advances in Mathematical Finance and Applications, 2018, **3**(3), P. 77-93. Doi: 10.22034/amfa.2018.544951
- [24] Ramazani, M., Ameli, A., *Forecasting of Stock Price Using Fuzzy Neural Network Based on GA and Comparison with Fuzzy Neural Network*, JEMR, 2016, **6** (22) P. 61-91.
- [25] Setayesh, M., Kazemnejad, M., *Effective Factors on Disclosure Quality of the Firms Listed in Tehran Stock Exchange*, Journal of Accounting Advances, 2012, **4**(1), P. 49-79. Doi: 10.22099/jaa.2012.514.
- [26] Yu, Lean, W., Lai, K., *Neural network-based mean–variance–skewness model for portfolio selection*, Computers & Operations Research, 2008, **35**(1), P. 34-46, Doi:10.1016/j.cor.2006.02.012
- [27] Yang, S., and Fu, L., *Critical chain and evidence reasoning applied to multi-project resource schedule in automobile R&D process*, International Journal of Project Management, 2014, **32**(1), P. 166-177. Doi: 10.1016/j.ijproman.2013.01.010.
- [28] Zamani, A., AnvaryRostamy, A., BadavarNahandi, Y., Saeedi, A., *The Effect of Agency Costs on the Speed of Stock Price Adjustment: Evidence of Tehran Stock Exchange*, Financial Management Strategy, 2018, **5**(4), P. 25-44. Doi: 10.22051/jfm.2018.15774.1403.