Int. J. Nonlinear Anal. Appl. In Press, 1–16
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2024.33406.4975

Financial bankruptcy prediction using artificial neural network and Firefly algorithms in companies listed in Tehran Stock Exchange

Mahdi Heidary[a], Shokrollah Ziari[b,*], Seyed Ahmad Shayannia[a], Alireza Rashidi Komijan[c]

[a]*Department of Industrial Management, Firoozkooh branch, Islamic Azad University, Firoozkooh, Iran*

[b]*Department of Mathematics, South Tehran Branch, Islamic Azad University, Tehran, Iran*

[c]*Department of Industrial Engineering, Firoozkooh Branch, Islamic Azad University, Firoozkooh, Iran*

(Communicated by Mouquan Shen)

Abstract

By anticipating financial turmoil, it is possible to take the necessary precautions before financial distress occurs by managers and investors. This study compares two algorithms for predicting bankruptcy using an Artificial Neural Network (ANN) and Neural network optimized metaheuristic Firefly Algorithm (FA). To run the test, initial values are first set for the network weights and biases. Then, during optimization, the FA algorithm generates a population of different weights and biases. The conversion function used in the output layer is linear, and a non-linear sigmoid function is selected for the middle layer. To conduct this research, the data of 79 companies listed on TSE from 2012 to 2015 were collected and analyzed statistically by backpropagation neural network and FA algorithms. The results show that FA, compared to ANN predicted the companies' bankruptcy much better. Also, the FA Algorithm maintains a good correlation between bankrupt and non-bankrupt companies, just like real data.

Keywords: financial bankruptcy, backpropagation neural network, firefly algorithm
2020 MSC: 37N40,92B20, 91G15, 68Q87

1 Introduction

Bankruptcy occurs when a company's debts exceed the value of its assets. In the stock exchange, the criteria for bankruptcy and the withdrawal of companies from the stock exchange is according to Article 141 of the Amended Commercial Law, which states that if at least half of the company's capital is lost due to losses, the board of directors is obliged to immediately call an extraordinary general meeting of shareholders to discuss the issue. The liquidation or survival of the company should be voted on. If the aforementioned assembly does not vote to liquidate the company, it must reduce the company's capital to the amount of the existing capital in the same meeting and following the provisions of Article 6 of this law. Bankruptcy prediction models establish a relationship between bankruptcy and several financial ratios, and one of the financial signs of bankruptcy is unfavourable financial ratios. Each ratio has

*Corresponding author
Email addresses: mah.heidary@yahoo.com (Mahdi Heidary), sh_ziari@azad.ac.ir (Shokrollah Ziari), sheibat@yahoo.com (Seyed Ahmad Shayannia), rashidi@azad.ac.ir (Alireza Rashidi Komijan)

Received: February 2024 *Accepted:* April 2024

a certain amount of predictive power, so the impending bankruptcy shows almost every dimension of the company's financial situation [10]. The occurrence of bankruptcy in companies is one of the most important topics in the field of financial literature. Because the occurrence of bankruptcy in companies, in addition to causing the loss of resources and capital of the companies, is also considered as a managerial weakness of the companies, on the other hand, the occurrence of bankruptcy has affected the beneficiaries, shareholders of the companies, creditors of the institutions and banks lending to the company. Therefore, by identifying these important factors in bankruptcy, managers can prevent bankruptcy by taking appropriate measures. The stock market is one of the important markets for directing the capital of the active participants in this market. This group is worried about the waste of their real and legal capital. Therefore, the discussion of identifying factors affecting bankruptcy is of particular importance for capital market participants. Bankrupt companies subject to Article 141 of the Commercial Law are subject to liquidation and have a significant negative impact on the capital market situation [23].

Bankruptcy exists as a fact in the important life cycle of modern commercial units and it is said that bankruptcy will lead to bearing heavy economic and social costs to shareholders, creditors, managers, employees and the economy as a whole. The macroeconomic policies of a country affect the financial performance of companies and their growth and development. Choosing the company's financing source is of fundamental importance in corporate governance and its future successful development. The capital structure and its adjustments can be affected by internal and external factors, which are called capital structure determinants. Internal factors and their effects can be managed by the company, but macroeconomic variables cannot be controlled by managers. Knowledge and awareness about the extent and direction of the influence of these factors on the capital structure helps company managers to make effective decisions about the capital structure with the aim of financial stability and sustainable growth [24]. Iqbal et al. [18] state that economic uncertainty negatively affects the performance of companies, which causes a decrease in return on assets, return on equity, gross profit, and thus implicitly increases the probability of bankruptcy. However, these studies have been expressed without using the bankruptcy rate based on economic data [29].

Predicting the financial bankruptcy of companies can be one of the important solutions to prevent the loss of financial resources. Financial bankruptcy can hurt the company itself, the national and global economy, and also a negative effect on unemployment and purchasing power parity [19]. In the financial literature, a company is considered financially helpless when it is unable to fulfil its obligations to creditors, if the financial helplessness of the company does not improve, it will lead to bankruptcy [17]. The importance of predicting bankruptcy is so great that many small and medium-sized businesses do not reach the growth process and fail in the early years of their activity, therefore, predicting the growth and decline of companies can be of cost. to prevent huge fees paid by entrepreneurs and companies in businesses [11]. The price-based bankruptcy forecasting model can be considered as an alternative to the accounting-based forecasting models such as the Altman and Olson model, which examines the bankruptcy of companies using information from the stock market. The basis of the bond pricing model is provided by Merton [22]; In this way, the developed model of K-MV bankruptcy prediction became known as Merton's K-MV model. Based on this model, the process of financial bankruptcy is estimated based on the net market value of the company's assets. Bankruptcy occurs when the market value of a company's assets is less than the value of its liabilities. Assuming the company's liabilities are zero if the market value of the company's assets at maturity exceeds the value of the bonds, lenders will receive a loan equal to the book value of the debt. Conversely, if the company's value is less than the bond's value at maturity, shareholders receive nothing and only lenders receive as much as the company's value. Therefore, the payment to creditors at maturity is equal to the book value of the bond minus the put option over the value of the firm's value, where the exercise price is equal to the book value of the bond and the maturity is equal to the bond's maturity date. Bankruptcy forecasting models based on accounting have a special priority compared to structural bankruptcy forecasting models such as those based on price because, unlike stock market price models, accounting models use the financial statements of companies and may be affected by real profit management. In an efficient market, investors are influenced by real profit management in the pricing process [25].

The issue of corporate bankruptcy is not specific to the public or private sector, in other words, state or private ownership is not a criterion for corporate bankruptcy. What is important is how these companies are managed. Perhaps there are large public companies that have programs with accurate production planning and correct financial and human resources structure, the company is managed in a way that not only does not need government aid and support but also in case of removing some government rents in the country's economy and amending currency and monetary laws, the economic situation It will get better and also there are some private companies that should declare bankruptcy as soon as possible if customs tariffs are revised or direct and indirect government aid is withdrawn. It is very important. This research tries to answer the question that which approach is more suitable for predicting the bankruptcy of companies admitted to the stock exchange? Is there a significant difference in the results of predicting the bankruptcy of companies admitted to the stock exchange with the combined approach of the artificial neural network optimized with the firefly algorithm and the data envelopment analysis algorithm or not? Also, these two models, introduce the model that is more efficient in the Tehran Stock Exchange.

2 Theoretical foundations and research background

Corporate bankruptcy usually affects capital market liquidity and economic development. During bankruptcy, banks typically reduce lending to bankrupt companies and charge higher interest rates on loans to companies to compensate for the additional risk. In the same way, investment institutions such as pension funds and insurance companies have reduced their stock purchases and are more likely to invest in and purchase bank bonds or similar markets. All these will reduce liquidity in the capital markets, increase the capital cost of companies and reduce economic growth [28].

By using financial statements, it is not possible to directly predict the bankruptcy of a company in the coming years, but by using models that have been created and defined by scientific-experimental methods and in other countries. If it has been implemented, it is possible to predict the bankruptcy of companies several years before its occurrence. If the financial situation of these companies is clarified through the model test and their bankruptcy can be predicted, the shareholders and managers will prevent the bankruptcy of that company to prevent bankruptcy or change to the correct situation [20]. In the Iranian capital market, the criteria for bankruptcy and exit of companies from the stock market is Article 141 of the Trade Law, this article states: "If at least half of the company's capital is lost due to losses, the board of directors is obliged to immediately hold a general assembly." To invite shareholders to vote on the issue of liquidation or survival of the company. If the aforementioned assembly does not vote to liquidate the company, it must reduce the company's capital to the amount of the existing capital in the same meeting and by the provisions of Article 6 of this law.

The probability of bankruptcy, which is interpreted as bankruptcy risk, although small, can increase the cost of financing the company from debt and equity. Therefore, the increase in bankruptcy risk is expected to affect the expected rate of return of the company's shareholders. As it was said, with the increase in financial leverage or the ratio of financing from debt, the risk of bankruptcy increases and decreases with the decrease of financial leverage. In addition, the higher the volatility of the company's assets, the higher the probability of the company's bankruptcy.

Theoretically, in several researches, the relationship between bankruptcy risk and the expected rate of return of shareholders has been examined, and contradictory results have been presented regarding the sign and significance of this relationship. On the one hand, studies such as Chava and Purnanandam [9] and Aretz et al. [5] have reported a positive relationship between bankruptcy risk and stock returns; On the other hand, some studies have found a negative relationship between bankruptcy risk and stock returns (bankruptcy anomaly), including Griffin and Lemmon [14], Campbell et al. [7], Garlappi and Yan [12]. Nomad [13].

Matsumaru et al. [21] support vector machine, artificial neural network and multiple discriminant analysis based on financial indicators, support vector machine is more accurate in predicting the risk of bankruptcy of companies than other models. Alexandropoulos et al. [2] using Dense Neural Network (DDNN) to predict the bankruptcy of Greek companies provided significant results.

Tang et al. [31] modified neural network with the evolutionary process for bankruptcy prediction of multilayer model (MLP) and the basic neural network model performs better in terms of accuracy, convergence speed and area under the curve of the proposed algorithm. Altman et al. [4] investigated five different models for predicting the financial disorder of small and medium-sized companies and found that logistic regression and neural networks are superior to other approaches. Stolbov and Shchepelev in [29] examine the causal relationships between systematic risk, economic uncertainty and corporate bankruptcy, subject to global fluctuations caused by the VIX index, in a sample of 15 advanced and large emerging market economies from January 2008 to June 2018. The results showed that the effective existence of systematic risk and economic uncertainty with the VIX index shapes the bankruptcy of companies. Also, the amount of attention banks pay to the private sector causes credit fluctuations and gross domestic product. Agustia et al. in [1] examined the impact of accrued interest management and business strategy on bankruptcy risk. Research on the financial data of 1,068 non-financial companies in the Indonesian Stock Exchange. The results showed that there is no relationship between earnings management and bankruptcy risk, while companies that implement one of the two general business strategies of cost leadership or differentiation significantly reduce bankruptcy risk. Habermann and Fischer in [16] examined the effects of corporate social performance on the probability of bankruptcy in times of economic growth. The probability of bankruptcy was measured by Altman [3] score and the social performance of the company was measured by Refinitiv ESG scores. Using static panel data regression and instrumental variable regression on a sample of 6,696 US firm annual observations from 2010 to 2019, the main findings are: (1) contrary to existing research, the level of corporate social performance appears to It does not seem to have a (positive effect) on the probability of bankruptcy during economic growth. (2) An increase in the social performance of a company during economic growth leads to an increase in the probability of bankruptcy. We conclude that the positive effects of corporate social performance on stakeholder relations are not realized in prosperous business environments. Therefore, the costs of increasing the social performance of the company exceed their immediate positive effects and increase the probability of bankruptcy.

2.1 Probability of bankruptcy using Ohlson's model

The qualitative traits used in the research use the Bernoulli distribution, a distribution that can cover only two states (victory or defeat). In Bernoulli, if the desired chance is considered as p and its alternative is q, the relation $q + p = 1$ must always be maintained. To quantify these attributes, we use dummy variables here. These variables can explain victory and defeat by fluctuating between values of one and zero. Variables that assume the values of one and zero are called dummy variables. The logit technique is used when we have only two states and the dependent variable is not visible. In logit, as in multivariable regression, the coefficients are estimated separately. In this connection, logistic regression assumes the S-shaped relationship as in diagram 1 between the probability of occurrence of a phenomenon (dependent variable) and a linear combination of independent variables [15].

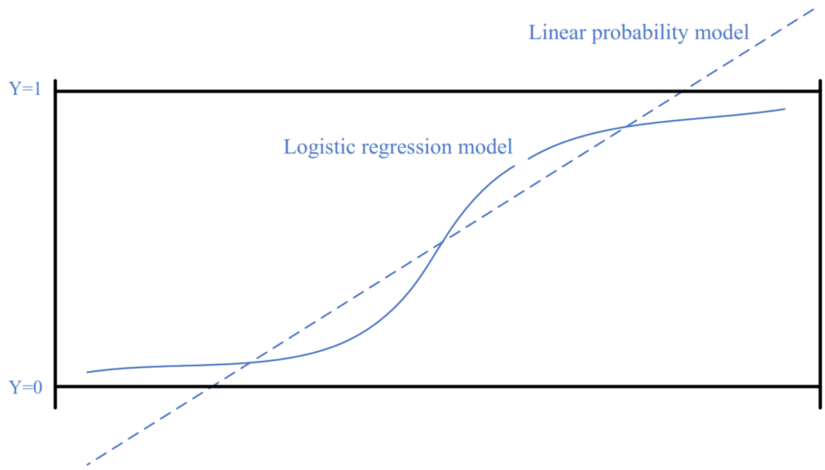

Figure 1: Logistic regression model

Here, to show descriptive variables, we use variables that the dependent variable is defined according to them.

$$Z = F(X_1, X_2, X_3, ..., X_n). \tag{2.1}$$

where, Z represents the financial status of the investigated companies. which shows whether a company is in the category of bankrupt or healthy. Of course, the choice of X depends to some extent on the researcher's opinion and his knowledge of the economic conditions. The reason for that is the different economic and financial structure of the countries in such a way that in some countries we see that one variable has a great contribution in determining, while in another country the same variable is of very little value and sometimes meaningless. Now if we assume that our model is as follows and the logit regression extraction for it will be as follows:

$$Z = \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + ... + \alpha_n X_n. \tag{2.2}$$

Based on the logit model, the figures obtained for Z should be put in the formula $P(Z) = 1/(1 + e^{-z})$ to calculate the conditional probability [26].

$$P_i = E(Y = 1|X_i) = 1/(1 + e^{-(z)}). \tag{2.3}$$

Probability of bankruptcy:

$$P^{-1} = E(Y = 1|X_i) = e^{-(z)}/(1 + e^{-(z)}). \tag{2.4}$$

2.2 Financial bankruptcy of companies based on Article 141 of the revised trade law

The financial bankruptcy of companies is based on Article 141 of the amended trade law, and the logistic regression model is used, in the models, it is a dependent variable (bankruptcy and non-bankruptcy); it is self-explanatory for the group of bankruptcy (more debts than assets) and non-bankruptcy, which choose values of zero and one respectively. To explain the phenomena whose dependent variable is an imaginary variable, the following model is used. The above equation is known as a logistic cumulative distribution function

$$p=\frac{1}{1+e^{-(\alpha+\beta_1X_1+\ldots+\beta_nX_n)}}. \tag{2.5}$$

2.3 Financial bankruptcy in the incremental model of data envelopment analysis

The incremental model of data envelopment analysis, which was first proposed by Charnes et al. [8], is a model designed to evaluate the level of efficiency or bankruptcy of a specific decision-making unit in relative comparison with other decision-making units. This model of data envelopment analysis in the years The latter has many applications and has been used in various researches, especially in the field of bankruptcy analysis [27, 30]. The general form of the incremental data envelopment analysis model for the DMU decision-making unit can be shown as the following relationship:

$$\begin{aligned}
&\min \sum_{i=1}^{k} S_i^{+}+\sum_{r=1}^{s} S_r^{-} \\
s.t.\quad &\sum_{j=1}^{n} x_{ij}\lambda_j+S_i^{+}=x_{ih} \qquad i=1,\ldots,k \\
&\sum_{j=1}^{n} y_{rj}\lambda_j+S_r^{-}=y_{rh} \qquad r=1,\ldots,s \\
&\sum_{j=1}^{n} y_{rj}\lambda_j=1 \\
&S_i^{+}\geq 0,\quad S_r^{-}\geq 0,\quad \lambda_j\geq 0.
\end{aligned} \tag{2.6}$$

3 Research hypotheses

Investors always want to avoid the risk of burning their capital by anticipating the possibility of bankruptcy of a company. Therefore, they are looking for methods by which they can predict the bankruptcy of companies because, in the event of bankruptcy, the stock price will fall sharply. In the Tehran Stock Exchange, the criteria for bankruptcy and withdrawal of companies from the stock exchange is Article 141 of the amended Trade Law. In this article, it is stated that "if at least half of the company's capital is lost due to losses, the board of directors is obliged to immediately call an extraordinary general assembly of shareholders so that the issue of liquidation or survival of the company can be discussed and voted on." If the aforementioned assembly does not vote to liquidate the company, it must reduce the company's capital to the available capital resources in the same meeting and by the provisions of Article 6 of this law.

Usually, various reasons cause bankruptcy, the most important reason for the bankruptcy of companies is the mismanagement of organizations. Management errors, high cost, poor financial activity, ineffectiveness of sales activity and high production cost can alone or a combination of them be a warning for the bankruptcy of the company.

Economic activities can be another reason for the bankruptcy of companies. Economic stagnation, changes in interest rates, high inflation, price fluctuations of raw materials and international economic conditions are among the economic reasons for the bankruptcy of organizations. Government decisions, unwanted natural support and the life stage of organizations are also other reasons for bankruptcy.

This research has no hypothesis and only aims to answer the following question:

"Does the prediction of corporate bankruptcy using the combined neural-firefly algorithm have less error than the classical neural network algorithm?"

4 Research methodology

This research is applied in terms of purpose, in terms of quasi-experimental information-gathering method, descriptive survey and post-event. Also, in terms of information-gathering tools, it is a library, and due to the nature of modelling and forecasting, it is an inductive research type. In this research, multilayer perceptron neural networks with error backpropagation algorithms have been used to detect the bankruptcy of companies. After screening the companies' data, a total of 79 companies' information in 2013 was used to predict their bankruptcy in 2013. Among the 79 sample companies, 39 companies are among the companies that went bankrupt in 2013 and the remaining 40 companies are among the companies that did not go bankrupt in 2013. The inputs of the network, as shown in Figure 2, are the current ratio, debt-to-equity ratio, net profit-to-equity ratio, working capital-to-total asset ratio, and debt collection period ratio.

To perform the test, first, an initial value for the weights and biases of the network is determined, and then during the optimization process, a population of different weights and biases are generated by the firefly algorithm. This population of answers moves towards the optimal point or optimal weights and biases in each repetition of the algorithm according to the mechanism provided in the meta-heuristic algorithm. Also, the output of the network is a neuron titled bankrupt or non-bankrupt, which shows a number between zero and one, that is, the probability of bankruptcy or non-bankruptcy of the company. Therefore, the neural network used has an input layer with 5 neurons and an output layer with 1 neuron in Figure 2.

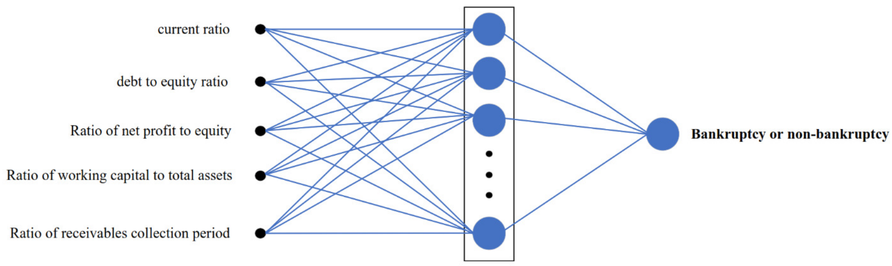

Figure 2: Inputs and outputs used in the neural network for bankruptcy prediction

Since one of the factors affecting the structure of the neural network is the number of neurons in the hidden layer, in the next section, the neural network with different numbers of neurons was used and the most optimal structure was selected for use. There are two different methods to train the network. In the first method, the weights and biases of the network are updated after providing the entire training data to the network, which is also called the mass training method. In the secondary method, the weights and biases of the network are updated after passing through each of the training data. The teaching method, which is also called ¬the online teaching method, is slower, but the possibility of convergence is greater.

Table 1: Neural network adjustment parameters used in this research

1×10^{-5}	Minimum gradient network training
1×10^{-2}	Minimum training error
0.05	Training rate
4	The maximum number of consecutive error increments allowed on the evaluation data
random	How to divide data
1000	Epoch number
mean squared error	Network performance function

In this research, due to the importance of speed in calculations, the mass training method has been used. Other parameters used in network training are presented in Table 1. A neural network with a single hidden layer was used to predict the bankruptcy of companies.

The tangent sigmoid excitation function is used for the hidden layers of the network. This excitation function is defined as follows:

$$y = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{4.1}$$

The diagram in Figure 3 shows the sigmoid tangent excitation function.

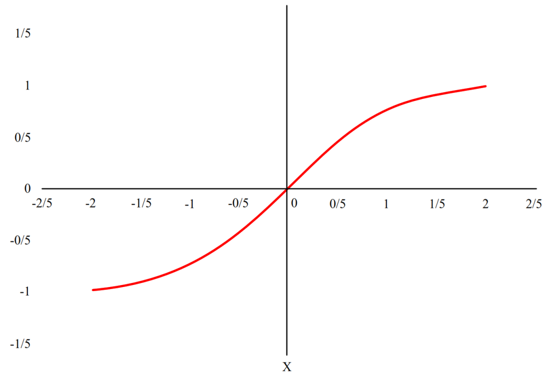

Figure 3: Sigmoid tangent excitation function

To choose the most optimal number of neurons in the single hidden layer of the network, the network was run with different numbers of neurons (between 1 and 20) and the amount of network error was calculated on the test data in each run. Since the weight values and initial biases of the network affect its performance, therefore, to eliminate this effect, the neural network was re-programmed 5 times for different values. The run is run in the hidden layer and the average error value for each number of neurons is used as a criterion to select the optimal number of neurons. Also, to evaluate the types of training methods used in the neural network, 9 different algorithms have been used to train the neural network and the mentioned procedure has been repeated for each algorithm. Figure 4 shows the average error of the network on test data for different numbers of neurons and different training algorithms.

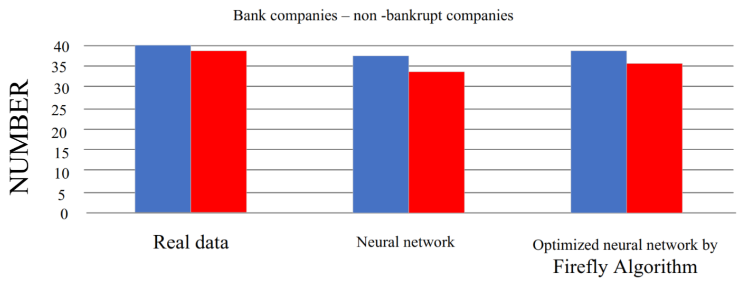

Figure 4: Average network error on the data tests according to the number of neurons Different hidden layers

As it is clear from Figure 4, the Levenberg-Marquardt algorithm has the lowest average error rate on the test data in the number of neurons equal to 6. Therefore, the neural network was trained with this algorithm and 6 neurons in its hidden layer until the best possible result was obtained. At this stage, to ensure the best result, the number of network iterations is increased to 5000 and the rest of the training parameters remain constant. Figures 5 and 6 show, respectively, the amount of network error on the training, testing and evaluation data, as well as the training gradient in different epoch values. Also, Figure 7 shows the error histogram for all three types of training, testing and evaluation data.

In this section, the weight and bias parameters of the neural network have been optimized by the Firefly algorithm. The general procedure is that first, an initial value for the weights and biases of the network is determined, and then during the optimization process, a population of different weights and biases is generated by the firefly algorithm. This population of answers tends to the optimal point (or optimal weights and biases) in each repetition of the algorithm according to the mechanism provided in the meta-heuristic algorithm. The data provided to the neural network is divided into two categories, training and testing, where 80% of the data are used for training and the remaining 20% are used as test data to evaluate the generality of the network. The objective function that is used for optimization by the firefly algorithm is actually the mean squared error function on the training data, which is defined as follows:

$$MSE_{train} = \frac{1}{n_{train}} \sum_{i=1}^{n_{train}} \sum_{j=1}^{2} er_{ij}^2 \tag{4.2}$$

in the above equation, the term n_{train} represents the number of data used in network training, er_{ij} represents the

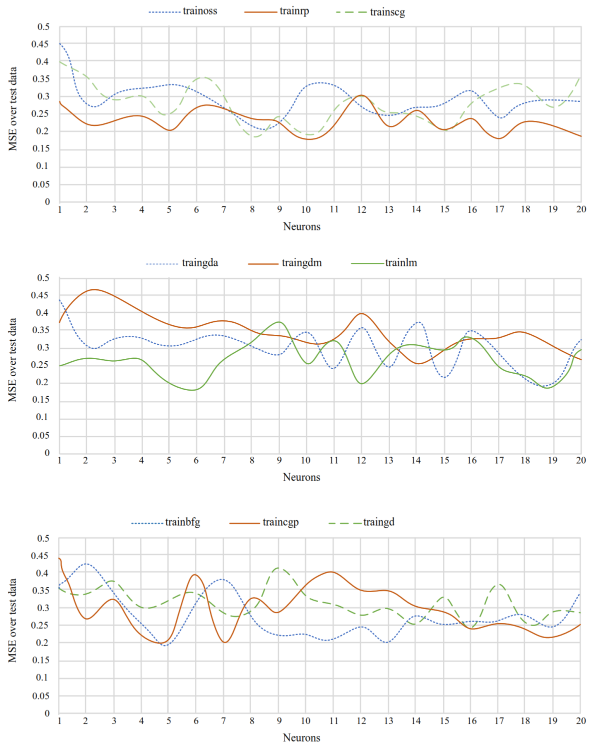

Figure 5: Graph of network performance (mean squared error) for training, testing and evaluation data

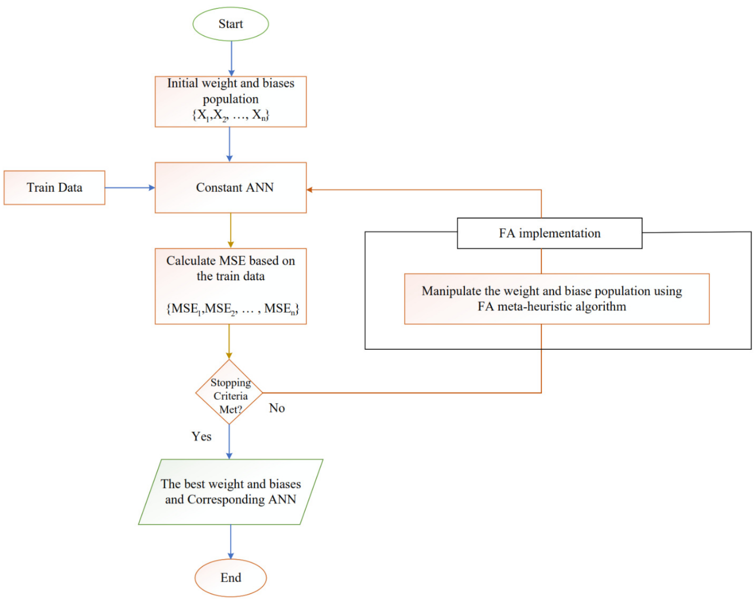

Figure 6: The gradient of network training in different Epoch values

error on the jth neuron and the ith training data. The variables that should be optimized by the firefly algorithm are the weights and biases of the neural network, which are defined as follows for a network with a single hidden layer

$$X = [x_{ij}]_{1\times n_{opt}}, \tag{4.3}$$

the parameter n_{opt} represents the number of unknown variables of the problem and is calculated as follows for the hidden single layer network:

$$n_{opt} = (m_1 + 1) \times N_n + (N_n + 1) \times m_2. \tag{4.4}$$

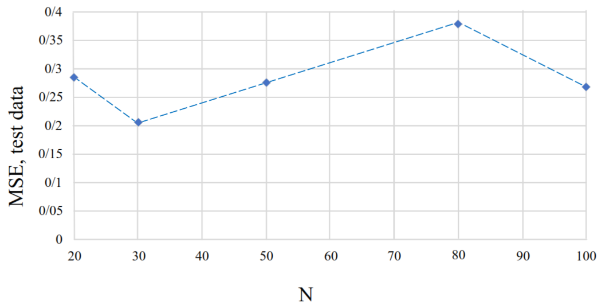

Figure 7: Error histogram for the data training, testing and evaluation of the neural network estimated by the Tema algorithm Levenberg-Marquardt

In the above equation, m_1 represents the number of neurons in the input layer and m_2 represents the number of neurons in the output layer, while the term N_n represents the number of neurons in the hidden layer. The number of input and output neurons of this problem are fixed and equal to 5 and 1, respectively. Considering that after trial and error and choosing different values of the number of neurons for the hidden layer of the neural network, the number of 6 neurons were selected as the optimal neurons, so the number of variables that should be optimized by the firefly algorithm will be equal to 33. which is the same number of weights and biases of a network with 5 inputs, one output and the number of 6 neurons in its hidden layer. The procedure used to optimize the neural network with a meta-heuristic algorithm is well shown in Figure 8.

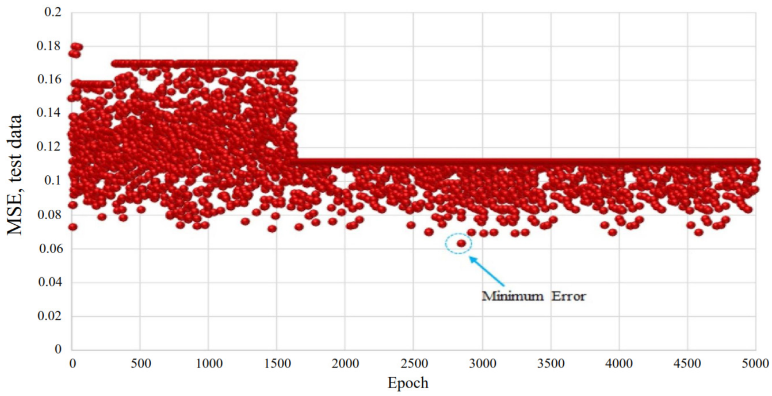

Figure 8: The procedure used to adjust the weights and biases of the neural network using the firefly algorithm

The parameters used in the firefly algorithm to optimize the weights and biases of the neural network were selected after trial and error and are presented in Table 2.

Table 2: The parameters used in the firefly algorithm to optimize the weight and bias of the neural network

β_0	γ	α	n_{iter}	$x_{\min}$	$x_{\max}$
1	3	0.25	1000	-3	+3

The parameter β_0 represents the initial brightness of fireflies and is considered equal to one in many articles. The parameter γ appears in the exponential term and although it can have a value between zero and infinity, its value is usually between 1 and 10. In this research, after choosing different values of γ and optimizing the neural network, the value of 3 was considered as the optimal value for this parameter. The α parameter represents the random movement of the firefly and after choosing different values, the value of 0.25 was chosen as the most optimal value; n_{iter} parameter represents the maximum number of repetitions to reach the optimal point in the firefly algorithm and it is considered equal to 1000 in this problem. Values of $x_{\min}$ and $x_{\max}$ represent the minimum and maximum values of the problem variables (weight and biases of the network) respectively, which are considered equal to -3 and +3, respectively.

One of the parameters affecting the performance of the Firefly algorithm is the number of particles used in the algorithm. To investigate the effect of the number of different particles on the performance of the algorithm, the firefly algorithm was run with different values of the number of particles to optimize the neural network and the results are presented in Figure 9. As it is clear from the figure, the grid error has no direct relationship with the number of particles and does not necessarily decrease with the increase of the number of particles. This problem can be attributed to the random nature of the firefly algorithm. The error of the network in the number of particles equal to 20 after passing the training data 1000 times has reached the value of 0.142, while this error value has increased to the value of 0.1433 for the number of particles equal to 30. Similarly, the minimum error obtained for the number of particles equal to 80 is equal to 0.1083, while the same value for the number of particles equal to 100 shows an increase of approximately 0.03. This problem indicates that the error of the optimized network does not depend on the number of particles used in the firefly algorithm.

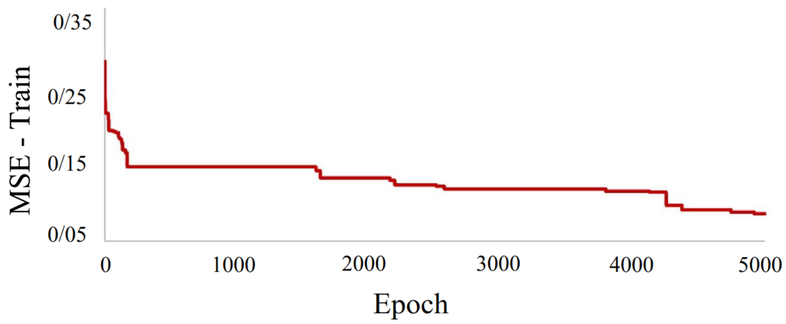

Figure 9: Neural network error estimated by nightworm theme algorithm

Swing on happened training in different amounts of particles used in the theme algorithm. Since in the discussion of the generality of the network, the error on the ¬test data is more important, the error value of the most optimal neural network obtained in each number of particles was calculated on the test data and the results in Figure 10 are drawn based on the number of particles. have been. As it is clear from the error results on the test data, running the algorithm with the number of particles equal to 30 has the lowest error on the test data. Therefore, in the next step, this number of particles was used in the firefly algorithm to train the neural network and its results were compared with the results of the neural network.

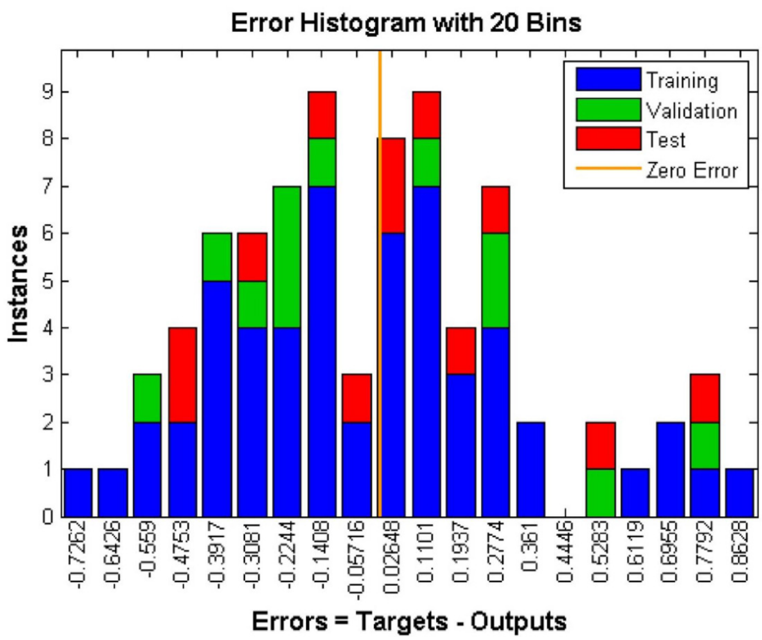

Figure 10: Neural network error to no based on the number of particles on the data tests

The firefly algorithm with the number of 30 particles and the parameters mentioned in table 3, except for the number of repetitions equal to 5000, is used to optimize the neural network, and the diagram in figure 11 shows the error of the network on the training data according to the number of repetitions. which is obtained after running the firefly algorithm several times to optimize the neural network.

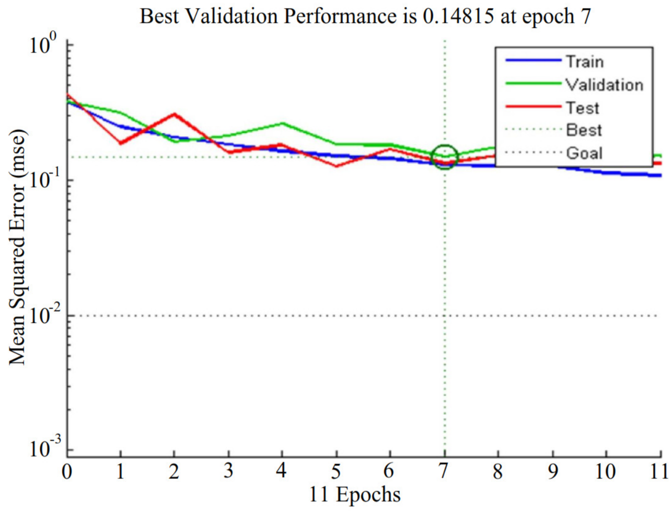

Figure 11: Neural network error estimated by nightworm theme algorithm swing With Number of 30 particles on basis number repeat r

As it is clear from Figure 11, the process of reducing the network error on the training data has always continued and in different amounts of repetition, although it has remained constant in certain time intervals. The best network error on the training data is obtained at the repetition value equal to 5000 and equal to 0.0851. The error of the neural network with the error obtained by the neural network optimized with the firefly algorithm is compared with each other in Table 3; As is clear, the neural network optimized with the meta-heuristic algorithm has less error than the normal neural network in the training, test and total data, which shows the optimality of its weights and biases.

Table 3: Error comparison between neural network optimized by classical algorithms and neural network optimized by firefly algorithm

	Optimized neural network by firefly algorithm	**Optimized neural network by algorithm based on derivative**
Mean squared error on training data	0.0851	0.1320
Mean squared error on test data	0.1051	0.1330
Mean squared error over all data	0.08915	0.1346

It should also be mentioned that in addition to the plan presented above to optimize the weights and biases of the neural network by the firefly algorithm, another plan based on the least error on the test data is also used to optimize the weights and biases of the neural network. The network was also used. The working procedure is such that the movement of the vector containing the weights and biases of the network in the search environment is based on the error function on the training data, while the characteristics of the particle that has the least error on the test data are used to adjust network weights and biases are used. Although an attempt was made to increase the generality of the network optimized by the firefly algorithm by applying this method, it was observed that despite the lower error of the network on the test data, the overall error of the network increased. The image presented in Figure 12 shows the error on the best particle in terms of test data. As it is known, the lowest error on the test data was obtained in repetition 2846 and equal to 0.06325. It can also be seen that the error on the test data in general has gone down from the number of repetitions approximately equal to 1700, which can be due to the transfer of particles to a place around the local optimal point compared to the test data.

It can be seen that although the optimal particle selected based on the test data has a mean squared error equal to 0.06325 on the test data, the same particle has an overall error of 0.1256 on all the data used (training and testing). which is much more than the error obtained using the original procedure. Therefore, in the continuation of the research, the results obtained by the initial design used for training the network using the firefly algorithm have been compared with the results obtained from the neural network optimized by classical algorithms. The number of bankrupt and non-bankrupt companies predicted by the neural network is compared with the results obtained by the neural network optimized with the firefly algorithm in Figure 13. While the neural network optimized by the firefly algorithm has not been able to identify only 3 of the bankrupt companies, the neural network optimized by the classical algorithm has not been able to identify 5 of the bankrupt companies well.

To compare the accuracy of the two methods used to predict the bankruptcy of companies, three parameters TPR,

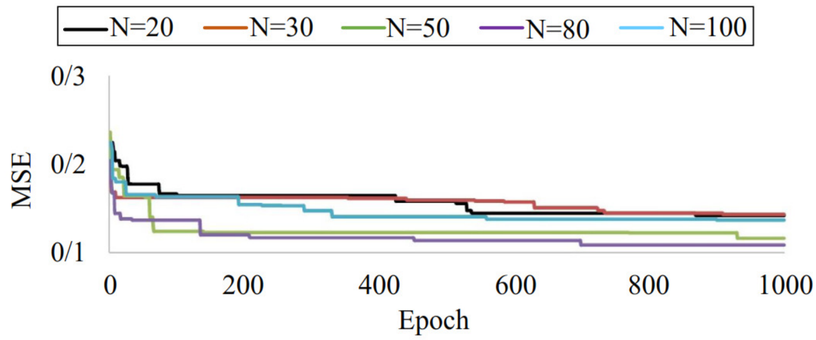

Figure 12: Grid error on test data for the best selected particle in each iteration

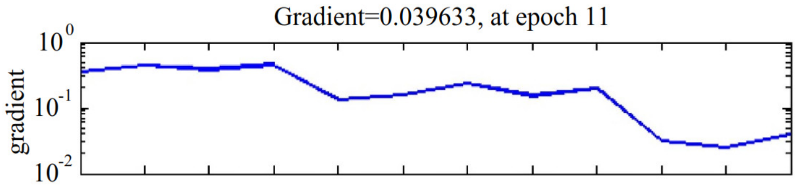

Figure 13: Comparison of prediction of corporate bankruptcy by neural network with neural network optimized by firefly algorithm

SPC and TCA have also been used. These two parameters are generally defined by the following equations:

$$TPR = \frac{TP}{TP + FN} \tag{4.5}$$

$$SPC = \frac{TN}{TN + FP} \tag{4.6}$$

$$TCA = \frac{TN + TP}{TN + FP + TP + FN} \tag{4.7}$$

The terms used in the above equations are defined as follows:

TP = correctly identified

FP = incorrectly identified

TN = correctly rejected

FN = incorrectly rejected

The term TP refers to the number of samples that are correctly selected as bankrupt companies by the model, while the term FP represents samples of bankrupt companies that could not be correctly selected by the network. The same definitions apply to the TN and FN terms, with the difference that non-bankrupt companies are considered in these terms. Based on this, these parameters for the two models presented in this research are presented in Table 4. According to the statistics presented in Table 4, the neural network optimized by the firefly algorithm shows a significant superiority over the neural network in two parameters, TPR and TCA. It is also observed -that while the classical neural network can correctly classify 90.5% of the companies, the neural network optimized by the firefly algorithm has been able to classify bankrupt and non-bankrupt companies with an accuracy of 94.2%. Estimate well. Therefore, according to the high accuracy of the total classification for the neural network optimized by the Firefly, it can be concluded that the use of the Firefly algorithm has been able to improve the performance of the neural network to estimate the bankruptcy of companies to a great extent.

Considering that the statistical data of 2013 was used to predict the bankruptcy of companies in the next two years using the neural network optimized by the Firefly algorithm, at this stage the financial data of 2013 related to 40 companies that did not go bankrupt in 2013 were used to predict the bankruptcy of these companies in 2014. For this purpose, the data of the current ratio, the ratio of working capital to total assets, the collection period of claims, the ratio of total debt to equity, and the ratio of net profit to equity for these companies in the mentioned year to the neural network optimized by Karam Shab algorithm. Tab was presented. The simulation results show that out of

Table 4: TPR and SPC terms for two different types of neural networks developed in this research

Statistical parameter / **The model used**	**Neural network optimized by Levenberg-Marquardt algorithm**	**Optimized neural network by firefly algorithm**
TPR, %	87.2	92.3
SPC, %	95	97.5
TCA, %	90.5	94.2

the total of 40 companies that did not go bankrupt in 2014, 10 companies will go bankrupt in 2015 according to the financial statistics of 2013.

5 Conclusion

The prediction of corporate bankruptcy started in the first half of the 20th century with the analysis of financial ratios. With the development of different types of these ratios, the investigation to assess the situation and predict the occurrence of financial helplessness and bankruptcy in companies intensified. Beaver [6] conducted the first classic univariate research to predict corporate bankruptcy, which is considered the basis of subsequent realizations in the same field. The most important result of Beaver's research was that financial ratios and, with a more general perspective, accounting information can be used as bankruptcy prediction tools. It is worth noting that the design of bankruptcy models is that most of them are based on the use of financial ratios as predictive variables. This problem caused that due to the existence of a wide range of financial ratios, regardless of the techniques used to design the models, which has led to the design of many models, the way to choose the final financial ratios for use in the models is also the diversity of this model. double the Research history shows that various methods such as factor analysis, diagnostic analysis, step-by-step method, correlation test between variables, paired t-test and even researcher's personal choice have been used for this purpose. It is also necessary to mention that the existence of different techniques in the field of bankruptcy prediction has caused researchers to test the possibility of combining different techniques to design a new model. Forecasting the financial bankruptcy of companies is considered one of the important issues in the field of financial decision-making, and considering the effects and consequences of this phenomenon at the micro and macro levels of societies, there are significant tools and models, each of which are different in the method or variable of prediction, has been presented at international levels. In this research, this prediction was made using the neural network model and firefly meta-heuristic algorithm. To evaluate the strength of neural networks and compare it with the firefly optimization algorithm, a multilayer perceptron model has been used. The results obtained from the research showed that bankrupt companies in the current ratio bankruptcy stages have a lower profit margin than non-bankrupt companies, which ultimately leads to a significant difference in the financial ratios of the two groups. In this research, the predictive ability of the neural network optimized with the Firefly algorithm is much higher and better than the classical neural network, and this shows that even though neural networks are better than different models such as Altman, Philosophy, Logit, logistic regression, Shiratau model, discriminant analysis and many tested models have a much higher ability to predict the bankruptcy of companies, but if the neural networks themselves are optimized with new meta-heuristic algorithms, the ability to predict is twice as high. As it was realized in this research, the optimized neural network with the firefly algorithm has shown a better and more acceptable result. Even though there has been much research abroad about predicting the bankruptcy of companies with different models and algorithms, few researches have been conducted in this field in our country and statistical models have been mainly used in the research. In foreign research, it can be seen that after presenting a model to a researcher, several years later these models have been tested by other researchers to check their applicability in the same economic environment, and most of the studies require adjusting the coefficients based on the new conditions of the same country are emphasized. However, it is expected that in the future, by using new techniques and variables, bankruptcy prediction models with high accuracy and easy understanding for users will be formed. The use of bankruptcy forecasting models will be a good guide for managers, investors and lenders to provide them with the necessary information before making a decision. Inefficient predictive models have been widely used by many stakeholders to predict bankruptcy, inability to pay loans and similar data. The higher the accuracy of the forecast model for a certain period, the more valuable that model is. Will was and of course value, its model to type 1 and 2 errors depend on the classification of bankrupt and non-bankrupt companies [4] considering the effects and consequences of financial bankruptcy at the micro and macro levels of societies, tools and Important models, each of which is different in the method and forecasting variables. In this research, this prediction is made using the backpropagation neural network model and the optimized neural network with the firefly meta-heuristic theme algorithm. the face took direction Evaluating the power of neural networks and comparing them with the theme algorithm for firefly nesting. Model Perceptron has been used several times. Expected that at the future, The first versions of the Firefly theme algorithm improvement data and further evaluations of its improved versions to solve real-world problems are expected in the future. From algorithm programs of the firefly theme that is used for large tasks, especially in the processing and analysis of large data. In this research, the predictive ability of the neural network optimized with the firefly theme algorithm much higher and better than back propagation neural network error is and this sign shows that with the existence of neural networks against different models such as Altman, Philosopher, Logit, logistic regression, Shirata model and discriminant analysis and many others. Among the tested models, it has a much higher ability to predict the bankruptcy of companies, but the neural networks themselves with algorithms of new meta-heuristic themes will have a higher ability for forecasting. The results of the present study show that network nervous with firefly theme allegory has shown a better and more acceptable result.

Considering that the statistical data of 2013 was used to predict the bankruptcy of companies in the next two years using the neural network optimized by the Firefly algorithm, at this stage the financial data of 2013 related to 40 companies that did not go bankrupt in 2013 were used to predict the bankruptcy of these companies in 2014. For this purpose, the data of the current ratio, the ratio of working capital to total assets, the collection period of claims, the ratio of total debt to equity, and the ratio of net profit to equity for these companies in the mentioned year to the neural network optimized by Karam Shab algorithm. The swing was provided. The simulation results show that out of the total of 40 companies that did not go bankrupt in 2013, 10 companies will go bankrupt in 2014 according to the financial statistics of 2013. Therefore, using the aforementioned financial ratios and the Firefly algorithm for a previous period of one to three years is useful, and it is recommended that capital market participants use this algorithm to predict the future financial instability of companies. Among the practical suggestions of the research is that important stock companies use the results of this research to prepare computer programs and software packages and guide the buyers of these companies' shares to make better purchases. The owners of the companies use the results of this research and get informed about the future status of their company before bankruptcy and take the necessary measures in case of bankruptcy. Stock exchange investors, banks and credit institutions should pay attention to this model for evaluating companies, accepting companies in the stock market and granting loans and facilities to them. Designing and establishing the software system of the neural network model and the firefly algorithm in predicting bankruptcy and connecting it to the stock exchange database to determine the degree of probability of bankruptcy of each company at any moment in time. Banks and monetary and financial institutions can use the results of this model as one of the items predicting the future status of companies to reduce the risk of non-fulfilment of obligations. Localization of models for predicting bankruptcy and financial helplessness of companies, according to the environmental conditions of Iran's economy. Investigating the impact of the inflation rate, bank interest rate and other economic influencing items on financial helplessness and bankruptcy forecasting models. Investigating the impact of these models in different industries for forecasting presented a bankruptcy model using variables that are not discussed in this research.

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