A Research on Pre-warning of Financial Risks of Water Enterprises Based on GWO-BP Neural Network

Xinyue Zhang, Liuliu Luo, Xumei Xiang, Yifan Meng, and Shicun Zhang(✉)

Business School of Hohai University, Nanjing, China
zsc202009@outlook.com

Abstract. BP neural network enjoys popularity in the field of pre-warning of financial risks, however, traditional BP network has problems like local minimum and slow convergence rate. Therefore, a new kind of BP network is in need. The GWO-BP network optimized by gray wolf algorithm becomes more popular and after tests, it shows that the new network has higher accuracy rate in the pre-warning of financial risks of water enterprises than the old one, which will fit the pre-warning model better in the operation.

Keywords: grey wolf algorithm · BP neural network · pre-warning of financial risks

1 Introduction

With the implementation of the "Water Ten Measures" (Action Plan for Water Pollution Prevention and Control) throughout the country, the demand for comprehensive water environment management continues to expand, and the policy orientation has directly brought the injection of social funds, thus China's water industry has maintained rapid development. As one of the most important urban basic service industries, water industry includes raw water collection and manufacturing, storage, transportation, water production and sales, sewage equipment production and manufacturing, sewage collection, discharge and treatment, sludge treatment and other links. Though water enterprises have experienced a rapid expansion and enterprise scale expanding, part of them only focus on the construction of the project, neglected the lack of budget control system, investment projects with unreasonable and high financing costs, they have not yet to establish a sound pre-warning mechanism of financial risks. In the long run, when the macro environment changes drastically and the water industry faces the cold winter of market, the water enterprises that have not formed a pre-warning of financial risks system will be difficult to deal with the operational risks leading to financial crisis.

At present, Chinese scholars have done some research on how to establish a pre-warning of financial risks mechanism. Zhou Shouhua [1], etc. (1996) combined the Z-score model with actual domestic situation, and established the F-score model to effectively warn the potential financial risks that business may face. In the recent past,

D. Kumar et al. (Eds.): IEIT 2023, AHSSEH 10, pp. 659–665, 2023.
https://doi.org/10.2991/978-94-6463-230-9_79

with the constant innovation of technology, the neural network model is increasingly used in the field of pre-warning of financial risks. Yang Baoan [2], etc. (2001) first put forward the idea of using BP neural network method to establish the financial crisis discrimination model, and applied it to the prediction of enterprise financial crisis, which can effectively avoid the influence of subjective factors of financial personnel, improving the accuracy of pre-warning, and has practical significance in the pre-warning of financial risks. However, traditional BP has problems such as small local formation and slow convergence rate, and the training effect is poor in case of less training data.

Using grey Wolf optimization algorithm (Grey Wolf Optimizer, GWO) to optimize BP neural network, with BP neural network weight and threshold as the grey Wolf positioning information, and based on the grey Wolf prey target positioning to constantly update positioning results, will make the model convergence speed up and enhance the accuracy, effectively avoid falling into local minimum, thus make the risk prediction more quickly and accurate. As a result, this paper employs GWO-BP neural network to give pre-warning of financial risks to water enterprises, which helps to improve accuracy in prediction and promote the effective control of financial risks in water enterprises' business activities.

2 Methodology

2.1 BP Neural Network

The BP neural network, also known as a multi-layer feed-forward neural network, is well-known for its forward-propagating signals and backward-propagating errors. Its concept was put forth by researchers led by Rumelhart and McCelland in 1986 and is applied in many different industries.

The input, hidden, and output layers of a BP neural network make up its three-layer processing structure. The number of nodes in the hidden layer of a BP neural network is typically determined using the empirical formula, whereas the number of nodes in the input and output layers of a BP neural network are determined.

However, there are still some defects in BP neural network, which shows that when using the BP algorithm to train weights, the purpose is minimized loss function, so it is simple to form the local minimum, resulting in different outputs. Therefore, at present, BP neural network is often combined with algorithms such as PSO and grey Wolf to optimize itself.

2.2 Grey Wolf Optimization Algorithm

The Grey Wolf Optimization Algorithm (Grey Wolf Optimizer, GWO) was named by Mirjalili et al., scholars at Griffith University in Australia in 2014 [3], which refers to the optimized search algorithm developed according to the characteristics of gray Wolf hunting activities. In this process, the Wolf pack was divided into four grades from high to low α, β, δ, and other gray wolf groups. These four grades correspond to the optimal, suboptimal, third optimal and other feasible solutions of the algorithm. Algorithmic mathematical model is written as [3]:

$$D_\alpha = \left| C \cdot X_p(t) - X(t) \right| \tag{1}$$

$$X(t+1) = X_p(t) - A \cdot D \tag{2}$$

where: D is the distance vector between individual gray wolves and the prey; t is the number of iterations; $X_p(t)$ is the position vector of prey; X(t) is the position vector of individual gray wolves; $A = 2a \cdot r_1 - a$, $C = 2 \cdot r_2$, r_1, r_2 is the random vector of module [0,1]; a is the convergence factor, which decreases linearly from 2 to 0.

Grey wolf populations have the ability to identify the location of the prey and surround them, which update the position vector of grey wolf individuals by calculating the position vectors of α, β, and δ packs [3]:

$$D_{\alpha,\beta,\delta} = \left|C_{1,2,3} \cdot X_{\alpha,\beta,\delta} - X\right| \tag{3}$$

where: X indicates the location of the current gray wolf individual; the distance from the current gray wolf individual [5] α,β,δ correspond to the values of 1, 2, and 3 of random vectors respectively.

$$X_{1,2,3} = X_{\alpha,\beta,\delta} - A_{1,2,3} \cdot D_{\alpha,\beta,\delta} \tag{4}$$

$$X(t+1) = \frac{1}{3}(X_1 + X_2 + X_3) \tag{5}$$

Equation (5) represents the final position vector of individual gray wolves in this round of update.

2.3 Improving the BP Neural Network with the Grey Wolf Algorithm

Based on the Grey wolf algorithm, traditional BP neural network has optimized itself and formed GWO-BP algorithm. Due to the poor selection of the initial value of BP neural network, the convergence rate is slow and easy to fall into the local minimum [5]. The GWO-BP will change the problem by using its magnificent ability of overall optimizing.

The specific steps to improving the BP neural network using the Grey Wolf optimization algorithm are as follows [4]:

Step 1: Data preprocessing.

Normalize the financial index data of listed water companies.

Step 2: Construct the structure of the BP neural network.

Determine the structure of the predicted neural network, including the number of input N_0, hidden N_n, and output N_m layer nodes. The normality test and factor analysis are used to analyze the initial index data set, and the cumulative contribution rate greater than 75% and the eigenvalue above 1 are selected as the feature variables, and the number of them was taken as the number of nodes in the input layer to predict the neural network model. The number of N_0 nodes is taken according to the empirical formula $N_n = \sqrt{N_0 + N_m} + a$; the number of N_m nodes in the output layer is valued according to the degree of financial risk.

Step 3: To set the GWO parameters.

Determine the number of wolves in the Wolf pack K, the maximum number of iterations T, the length d of the individual code of the weight and the threshold, and form the dimension matrix $(1 \times d)$.

Step 4: To determine the pack location.

The location vector $X(X_1, X_2, \ldots, X_k)X_i$ that produces the pack, which is the location vector for each grey Wolf (i. e., individual code). The position vector of the initial wolf pack is generated by formula (6) [4]:

$$X_i = l_b + r \times (u_b - l_b) \tag{6}$$

In Eq. (6), X (the individual position vector of the gray Wolf) corresponds to the weights w and thresholds b in the BP network. The length of the individual code of X is the sum of the number of weights and thresholds, and r is the vector of random numbers between [0, 1].

Step 5: Calculate the fitness.

The fitness function is determined by adding the absolute value of the error between the predicted value and the actual output value, as in formula (7):

$$\mathrm{fit} = R\left(\sum_{i=1}^{n} |Y_i - Z_i|\right) \tag{7}$$

In Eq. (7), n is the number of nodes in the output layer; Y_i is the actual financial risk degree value of the i node, Z_i is the predicted output value of the risk degree of the i node, R is the constant coefficient.

Step 6: Update the fitness values of the gray wolf position vector in the pack.

Calculated the three best fitness wolf information from the first iteration and saved as:

$$G_\alpha = \mathrm{fit}_{best};\ G_\beta = \mathrm{fit}_{second};\ G_\delta = \mathrm{fit}_{third} \tag{8}$$

In Eq. (8): the three position vectors fit_{best},fit_{second},fit_{third} respectively represent the highest fitness score in this iteration. After updating the position vector of the three grey wolves with the best fitness, the new wolf position vector after the next iteration is calculated by formula (7)–(8).

Step 7: Judge whether the optimization conditions are achieved.

Using the maximum expected error value ε, if the number of iterations does not reach T and the error of the two adjacent training results is not less than ε, return to step 4; otherwise, the optimal grey Wolf position vector is output X_α.

Step 8: Construct the GWO-BP neural network.

According to the α Wolf's X_α, the optimized weights $\left(w_1, w_2, \ldots, w_p\right)$ and thresholds $\left(b_1, b_2, \ldots, b_q\right)$ are determined, and the BP neural network is assigned as the initial weights and thresholds to complete the GWO-BP neural network construction.

Step 9: Financial risk degree prediction output.

The relevant data of the existing financial indicators are input into the GWO-BP neural network model, and the output results are the predicted value of the financial risk degree.

3 Establishment and Analysis

3.1 Selection of Indicators

Based upon the results of previous researchers' studies on the pre-warning model of financial risks neural network, seven financial indicators, which are operating profit per share, cash ratio, corporate cash flow, interest guarantee ratio, cash satisfaction investment ratio and main business profit ratio, are selected to establish the financial early warning system by factorial analysis. Using the net profit index for the years 2019–2021, the financial risk degree is divided into three risk degrees: low risk, medium risk and high risk.

3.2 Data Preprocessing

All the sample data are from CSMAR database, and the financial data of 89 representatively listed water enterprises in 2020 are selected. The data of these 89 water enterprises in 2020 are randomly divided into 40 training groups and 49 test groups, as a result, the test groups' predictions are used to assess the financial warning model's prediction accuracy. Data need normalized pre-procession before inputting in order to maintain the same metric scale, allowing the training neural network to converge faster. The data normalization formula is:

$$y_i = \frac{x_i - avgx_i}{\sigma_i}$$

3.3 GWO-BP's Design

The model is configured as a fundamental three-layer BP neural network with input layer, hidden layer, and output layer based on the accuracy of financial risk prediction. The seven financial indicators chosen by factor analysis as being the most explanatory of the company's operating capacity make up the number of nodes in the input layer. The output layer is 1 node, and the output results 1, 2 and 3 indicate the three conditions of low risk, medium risk and high risk respectively. The hidden layer determines the accuracy of the training. Too few layers will lead to poor training results, and too many layers will lead to "overfitting", so the 3–12 layers are selected according to the empirical formula. After several times of training, it shows that the optimal hidden layer for BP neural network is 10 layers, while for GWO-BP, the number is 12 layers. The weights and thresholds are optimized by GWO. The learning rate has an optimization range of [0, 0.01], while the optimization range of the number of iterations is an integer within [1, 20].

3.4 Training and Verification of the Pre-warning Model

This paper trains and tests the risk pre-warning model of water enterprises through MATLAB2018 to detect whether the model achieves the optimization effect. The BP neural network and the GWO-BP neural network were trained using 40 sets of data

Table 1. Prediction results of BP neural network and GWO-BPO neural network

	(a) BP neural network			(b) GWO-BP neural network		
	Low Risk	Medium Risk	High Risk	Low Risk	Medium Risk	High Risk
Sample Size	43	3	3	43	3	3
Number of Misclassifications	2	3	2	1	2	1
Judgment Accuracy	95.34%	0%	33.3%	97.7%	33.3%	66.7%
Overall Accuracy	85.71%			91.84%		

randomly selected before. Two sets of ideal network architectures, 7-10-1 and 7-12-1, were identified after examining the convergence rate and training prediction accuracy of each neural network. The test group is verified to test the prediction accuracy of the model. The specific results of the testing sets are shown in Table 1.

Table 1 demonstrates that the prediction accuracy of the BP neural network based on testing samples is 85.71%. It is still challenging to effectively predict medium risk and high risk samples with huge errors, despite the BP neural network's great fitting ability and high fit to low risk data. The prediction accuracy of the GWO-BP neural network based on testing samples is 91.84%. It can be seen that its ability to anticipate medium and high financial risk has increased.

The comparison of the classic BP neural network's findings with those of the GWO-BP neural network algorithm reveals that the GWO-BP neural network has further enhanced the local minimum, resulting in high training accuracy and superior training outcomes.

4 Conclusion

Based on the BP neural network and GWO-BP neural network algorithm, seven financial indicators representing five capabilities, such as profit and operation, are chosen to train the data of water enterprises in 2020. Compared the prediction results of traditional BP network and GWO-BP network with the real value of these water enterprises, GWO-BP neural network algorithm can achieve the purpose of forecasting water listed companies significant financial risk in actual scenario. Also, the results of the GWO-BP neural network prediction algorithm's enterprise financial risk prediction are more accurate than those of the conventional BP neural network algorithm.

References

1. Zhou Shouhua, Yang Jihua, Wang Ping. On the early warning analysis of financial crisis —— F score model [J]. Accounting Research, 1996 (08): 8-11.

2. Yang Baoan, Ji Hai, Xu Jing, etc. Application of BP neural network in enterprise financial crisis warning [J]. Forecast, 2001 (02): 49–54 + 68.
3. Mirjalili S, Mirjalili S M, Lewis A. Grey wolf optimizer [J]. Advances in Engineering Software, 2014, 69: 46-61.
4. Hou Yongyan, Yang Ao, Guo Wenqiang, Zhang Dong, Shi Shuai. Prediction of short-term power generation of neural network based on grey Wolf algorithm optimization [J]. Journal of Shaanxi University of Science and Technology, 2022, 40 (04): 171-177.
5. Cao Ke, Tan Chong, Liu Hong, Zheng Min. Wireless sensor network data fusion algorithm for optimizing BP neural network based on improved grey Wolf algorithm [J]. Journal of the University of Chinese Academy of Sciences, 2022, 39 (02): 232-239.
6. Zhang Wensheng, Hao Ziqi, Zhu Jijun, Du Tian tian, Hao Huimin. Short-time traffic flow prediction model for optimizing BP neural network based on the improved Grey Wolf algorithm [J]. Transportation System Engineering and Information, 2020, 20 (02): 196–203.
7. Shweta Sankhwar; Deepak Gupta; K.C. Ramya; S. Sheeba Rani; K. Shankar; S.K. Lakshmanaprabu. Improved grey wolf optimization-based feature subset selection with fuzzy neural classifier for financial crisis prediction[J]. Soft Computing: A Fusion of Foundations, Methodologies and Applications, 2020, (5)
8. Zhai Meijia. Risk Prediction and Response Strategies in Corporate Financial Management Based on Optimized BP Neural Network [J]. COMPLEXITY, 2021,
9. Bao Wei, Ren Chao. Research on battery SOC prediction method based on GWO-BP neural network [J]. Computer Applications and Software, 2022, 39 (09): 65-71.