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Research on Credit Risk Prediction Method of Blockchain Applied to Supply Chain Finance

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Abstract

INTRODUCTION: From the perspective of blockchain, it establishes a credit risk evaluation index system for supply chain finance applicable to blockchain, constructs an accurate credit risk prediction model, and provides a reliable guarantee for the research of credit risk in supply chain finance.
OBJECTIVES: To address the inefficiency of the current credit risk prediction and evaluation model for supply chain finance.
METHODS: This paper proposes a combined blockchain supply chain financial credit risk prediction and evaluation method based on kernel principal component analysis and intelligent optimisation algorithm to improve Deep Echo State Network. Firstly, the evaluation system is constructed by describing the supply chain financial credit risk prediction and evaluation problem based on blockchain technology, analysing the evaluation indexes, and constructing the evaluation system; then, the parameters of DeepESN network are optimized by combining the kernel principal component analysis method with the JSO algorithm to construct the credit risk prediction and evaluation model of supply chain finance; finally, the effectiveness, robustness, and real-time performance of the proposed method are verified by simulation experiment analysis.
RESULTS: The results show that the proposed method improves the prediction efficiency of the prediction model.
CONCLUSION: The problems of insufficient scientific construction of index system and poor efficiency of risk prediction model of B2B E-commerce transaction size prediction method are effectively solved.

Keywords: blockchain technology, supply chain finance credit risk prediction, jellyfish search optimisation algorithm, deep echo state network

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1. Introduction

With the rapid development of e-commerce and network technology, supply chain competition is also gradually obvious [1]. Supply chain finance as the current enterprise survival and development have to pay attention to the link, a large number of enterprises based on their own conditions and circumstances to put forward targeted financing needs [2]. With the increase of supply chain nodes and links, the model is constantly enriched, the structure is constantly complex, the nodes of the information exchange, financial transactions, product logistics and other methods of the frequency of exchanges is increasing, the difficulty of data processing is rising [3]. Blockchain technology, as an emerging computer technology, for the current difficult problems of financial credit risk, puts forward the evaluation method of supply chain financial credit risk field based on blockchain, which not only supplements the current blank of the application of blockchain technology in the field of financial credit risk evaluation, but also improves the financial institutions' risk assessment method, and also realises the rapid development of supply chain finance in the unimpeded flow of funds [4]. Therefore, from the perspective of blockchain, it establishes a credit risk evaluation index system for supply chain finance applicable to blockchain, constructs an accurate credit risk prediction model, and provides a reliable guarantee for the research of credit risk in supply chain finance [5].

Credit risk prediction of supply chain finance combined with blockchain is a complex problem, with more factors affecting risk prediction and evaluation, no regularity in the data distribution of the influencing factors, and uncertainty in the correlation [6]. Research on blockchain-based supply chain financial credit risk prediction and evaluation should not only study the construction of blockchain-based supply chain financial credit risk evaluation index system, but also study the algorithms and methods of constructing blockchain-based supply chain financial credit risk prediction model [7]. Currently, supply chain finance credit risk prediction and evaluation methods include grey prediction model [8], linear regression model [9], support vector regression [10], machine learning methods [10], deep learning methods [11], etc. Literature [12] applies blockchain technology to the supply chain smart contract aspect and proposes a credit risk prediction method for supply chain finance based on grey theory; Literature [13] researches the method of combining blockchain technology with the actual needs of enterprises based on the underlying technology of Bitcoin and using the transparency of the transaction information; Literature [14] researches the supply chain architecture based on the blockchain technology, and proposes the supply chain process optimization method; Literature [15] proposed a financial credit risk prediction method based on improved machine learning method through the perspective of global supply chain product security and challenges; Literature [16] proposed blockchain-based encryption technology and studied the evaluation and analysis method of the corresponding technology; Literature [17] predicted the supply chain financial credit risk by analyzing the supply chain financial credit risk influencing factors and adopting the artificial neural network method to predict the supply chain finance credit risk and responds to enterprise demand in real time. According to the analysis of the above literature, the existing credit risk prediction methods of supply chain finance have the following defects:

1) The selection of factors influencing the prediction of credit risk of supply chain finance is not comprehensive enough, and the construction of the index system is not scientific enough [18];

2) Lack of credit risk prediction and evaluation methods for supply chain finance based on blockchain technology [19];

3) There are fewer studies on credit risk prediction and evaluation in supply chain finance and the algorithms for constructing risk prediction models are less efficient [20].

With the development of computer technology, blockchain technology, machine learning methods, deep learning algorithms, intelligent optimisation algorithms continue to develop, and the combination of deep learning algorithms and intelligent optimisation algorithms makes the prediction and evaluation effective, making the research of supply chain financial credit risk prediction model based on intelligent optimisation algorithms to improve the depth of the learning network to become a hot spot of experts' research [21]. Aiming at the problems existing in the current supply chain financial credit risk prediction and evaluation methods, this paper proposes a supply chain financial credit risk prediction and evaluation method based on the intelligent optimisation algorithm to improve the deep echo state network. The main contributions of this paper are:

1) studying the supply chain financial credit risk prediction problem based on blockchain technology, analyzing the influence factors of supply chain financial credit risk prediction, and constructing the evaluation index system of supply chain financial credit risk prediction;

2) using the kernel principal component analysis technology to carry out dimensionality reduction analysis on the supply chain financial credit risk prediction index based on blockchain technology;

3) using the framework of system construction - feature dimensionality reduction-model establishment framework, combined with intelligent optimisation algorithm and deep echo state network method, to construct supply chain financial credit risk prediction model and evaluation method based on blockchain technology;

4) verified that the method in this paper has higher prediction accuracy and real-time performance through simulation.

2. Analysis of Credit Risk Prediction Problems in Supply Chain Finance Based on Blockchain Technology

In order to objectively, systematically and scientifically study the supply chain financial credit risk prediction problem, this paper analyses the supply chain financial credit risk prediction influencing factors and constructs the supply chain financial credit risk prediction evaluation index system by studying the supply chain financial credit risk prediction problem based on blockchain technology.

2.1. Description of the problem

Supply chain finance credit risk refers to the probability of the impact of the failure of each node enterprise to complete the required repayment due to various factors and the damage to the interests of other enterprises and the supply chain as a whole when they are financed through supply chain finance [22]. The main sources of supply chain finance credit risk (as shown in Figure 1) include: 1) SMEs' operating conditions; 2) core enterprise credit risk; 3) supply chain trade and operations; and 4) pledged material risk.

Figure 1. Credit risk sources in supply chain finance

Blockchain is a new application mode of computer technology such as distributed data storage, peer-to-peer transmission, consensus mechanism, encryption algorithm and so on [23]. This paper argues that blockchain is composed of many blocks, which automatically form a chain according to the time of generation, and does not rely on other institutions to provide credit evaluation, but rather, cryptography, computer science and other technologies are used as a means of guaranteeing security to build a corresponding secure shared database.

2.2. Principles of indicator selection

When blockchain technology is introduced into supply chain finance, the previous financial credit evaluation index is no longer applicable. Blockchain technology encrypts and uploads the transaction information of each node in the supply chain to each node through computer technology, so that all the enterprises in the chain can intuitively and transparently view the transaction records, avoiding the small problems of individual enterprises from becoming big problems in the supply chain [24]. For the re-selection of each indicator, this paper analyses the principle of indicator selection, as shown in Figure 2. Specific indicator selection principles are as follows: 1) **Comprehensiveness**. The content of credit risk evaluation indicators should be comprehensive, correctly reflecting the actual operating conditions of the enterprise, and showing the current situation of the enterprise from multiple perspectives and at a deep level; 2) **Scientific**. Each indicator selection should independently reflect the actual situation of a certain aspect of the enterprise, while adopting a scientific approach to the indicators and retrograde screening; 3) **Relevance**. It is necessary to reasonably select blockchain-related indicators for the characteristics of blockchain technology; 4) **Operability**. The selected indicators should achieve quantitative treatment and try to avoid being too subjective.

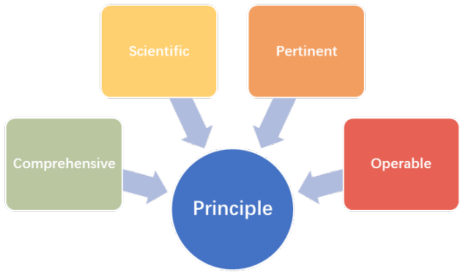


Figure 2. The principle analysis

2.3. Financial credit risk prediction impact indicators

As blockchain technology is less applied in the field of supply chain finance, this paper demonstrates the current situation of enterprises through their operating conditions and financial indicators. The financial credit risk prediction impact indicators mainly start from four aspects, including small and medium-sized financing enterprises, core enterprises, supply chain relationship, and enterprise assets.

(1) Small and medium-sized financing enterprises

Indicators on the part of small and medium-sized financing enterprises include management level of managers, profitability (return on net assets, net operating margin), operating capacity (total profit ratio, inventory turnover times, accounts receivable turnover), solvency (quick ratio, current ratio, interest coverage multiple, gearing ratio), development capacity (net profit growth rate, total asset growth rate), sales capacity (sales staff turnover rate , net sales margin), innovation ability (proportion of technical staff, new technology preparation rate, R&D investment intensity) [25].

(2) Core business aspects

Core business-related indicators include solvency (shareholders' equity ratio) and creditworthiness (credit rating).

(3) Supply chain relationship aspects

The supply chain relationship aspect of the indicator refers to the relationship strength, i.e., the frequency of transactions.

(4) Aspects of business assets

Indicators on the asset side of the enterprise include the condition of the assets, i.e., inventory turnover, accounts receivable period, and return on invested capital.

The specific structure of the financial credit risk prediction impact indicators is shown in Figure 3.

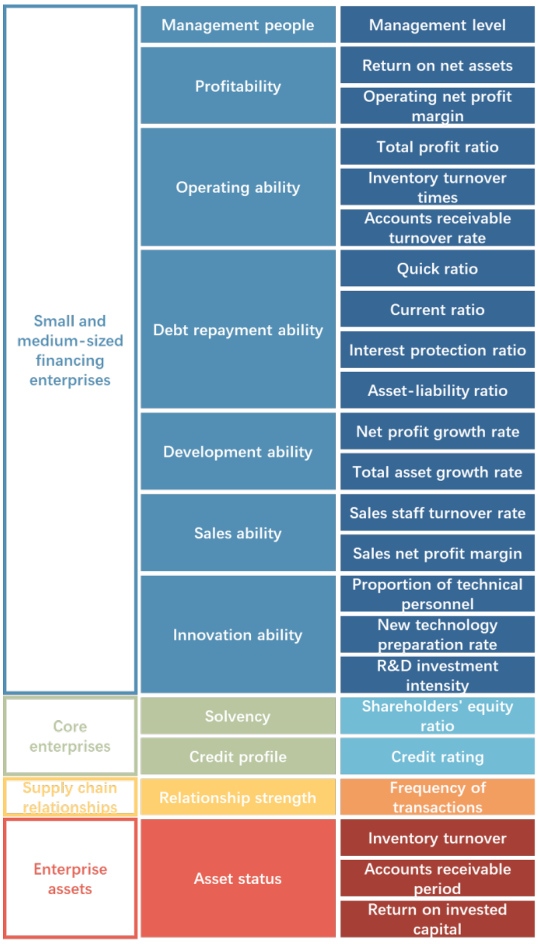


Figure 3. Structure of financial credit risk prediction impact indicators

2.4. Evaluation system construction

The financial credit risk prediction impact indicator system combining blockchain technology is based on four aspects of small and medium-sized financing enterprises F1, core enterprises F2, supply chain relationship F3, and enterprise assets F4, with management personnel F11, profitability F12, operating ability F13, small and medium-sized financing enterprises' solvency F14, development ability F15, sales ability F16, innovation ability F17, core enterprises' solvency F21, credit standing F22, relationship strength F31, and asset position F41 as secondary indicators, and management level X1, return on net assets X2, net operating margin X3, total profit ratio X4, inventory turnover X5, accounts receivable turnover X6, quick ratio X7, current ratio X8, interest coverage multiple X9, gearing ratio X10, and net profit growth rate X11, Total Assets Growth Rate X12, Sales Staff Turnover Rate X13, Net Sales Interest Rate X14, Technical Staff Weight X15, New Technology Preparation Rate X16, R&D Investment Intensity X17, Shareholders' Equity Ratio X18, Credit Rating X19, Transaction Frequency X20, Inventory Turnover Ratio X21, Accounts Receivable Accounting Period X22, and Return on Invested Capital X23 as the tertiary level indexes, which fully embodies the The whole process of financial credit risk prediction combined with blockchain technology, constructing a scientific, objective, comprehensive and reasonable system of influencing factors of financial credit risk prediction combined with blockchain technology.

3. Related Technologies

3.1. Kernel Principal Component Analysis Method

In order to extract the principal components of B2B e-commerce transaction size prediction influencing factors, this paper adopts the Kernel Principal Component Analysis (KPCA) [26] method for feature extraction and dimensionality reduction of the influencing factors.KPCA is an improvement of the principal component analysis method, which uses the kernel function for constructing the complex nonlinear classifiers. The core idea of KPCA is to use the kernel function to map the original data to a high-dimensional feature space and then perform PCA in that space.The specific steps are as follows:

Step 1: Standardised processing of indicator features. In order to eliminate the difference in scale between different impact factors, the original data matrix is standardised, and the standardised matrix Z is obtained by using the Z-Score method, where n is the number of samples, and d is the dimension of the sample indicator characteristics.

Step 2: Calculate the correlation coefficient between each indicator expressed by equation (1).

$$\sigma_{ij} = \frac{\sum_{k=1}^{n}\left(z_{ki}-\bar{Z}_i\right)\left(z_{kj}-\bar{Z}_j\right)}{\sqrt{\sum_{k=1}^{n}\left(z_{ki}-\bar{Z}_i\right)^2\left(z_{kj}-\bar{Z}_j\right)^2}} \tag{1}$$

In equation (1), z_{ki} denotes the standardised value of the ith indicator for the kth sample; $\bar{Z}_i$ is the mean value of the ith indicator; σ_{ij} is the covariance of the vectors Z_i and Z_j.

Step 3: Select the Gaussian kernel function as the kernel function and calculate the kernel function value Eq. (2):

$$K\left(z_i, z_j\right) = \exp\left(-\gamma\left\|z_i - z_j\right\|^2\right) \tag{2}$$

where γ is the Gaussian kernel function parameter that controls the distribution of data points in the high dimensional space.

Step 4: Compute the diagonal matrix Λ of the symmetric positive definite matrix K to obtain the characteristic roots $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_d$.

Step 5: Determine the contribution of the matrix K . Calculate the contribution of the ith principal component ω_i :

$$\omega_i = 1 \Big/ \sum_{j=1}^{d} \lambda_j \tag{3}$$

Step 6: Determine the number of principal components *k*. Sort the components one at a time according to the magnitude of the contribution rate, determine the information retention threshold after decoupling α , and if the cumulative contribution rate of the first k components ρ is greater than α , then the number of principal components is k.

$$\rho = \sum_{i=1}^{k} \omega_i \tag{4}$$

Step 7: Output the *k* indicator features associated with the principal components.

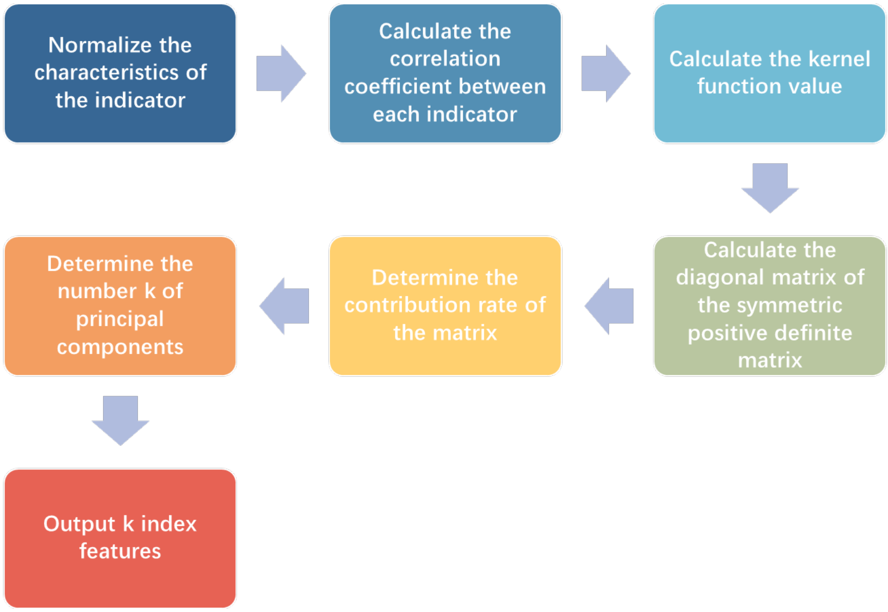


Figure. 4. Flowchart of KPCA method

3.2. Deep Echo State Networks

In order to solve the problem of tactical manoeuvre meta-prediction in the long time domain, a deep echo state network (DeepESN) based on a self-encoder is proposed in this section.

Echo state network (ESN) [27] is a kind of recursive neural network, using the "reserve pool" method to build the network hidden layer, usually used for time series prediction [189] . ESN is mainly composed of the input layer, the storage layer, the output layer, the specific structure is shown in Figure 5. The connection weights from the input layer to the storage pool $\boldsymbol{W}_{in}^{r\times n}$ are not trained and will not be changed after the initial randomisation. The reserve pool input comes from the output of the previous state of the input layer and the reserve pool respectively, and the state feedback weight $\boldsymbol{W}^{r\times r}$ is randomly initialised and does not need training. Reserve pool to the output layer weights $\boldsymbol{W}_{out}^{m\times r}$ need to be trained, generally using Ridge regression (Ridge regression) method for connection weights, which is expressed as equation (5):

$$\boldsymbol{W}_{out} = \boldsymbol{Y}_{long} \boldsymbol{H}^T \left(\boldsymbol{H}\boldsymbol{H}^T + \lambda_r \boldsymbol{I} \right)^{-1} \tag{5}$$

Where $\boldsymbol{H}$ is the storage pool state and λ_r denotes the regularisation factor. The state of the storage pool $\boldsymbol{H}$ is shown in equation (6):

$$\boldsymbol{H}(t) = \tanh\left(\boldsymbol{W}_{in} \boldsymbol{X}_{long}(t) + \boldsymbol{W}\boldsymbol{H}(t-1) \right) \tag{6}$$

where tanh denotes the hyperbolic tangent activation function.

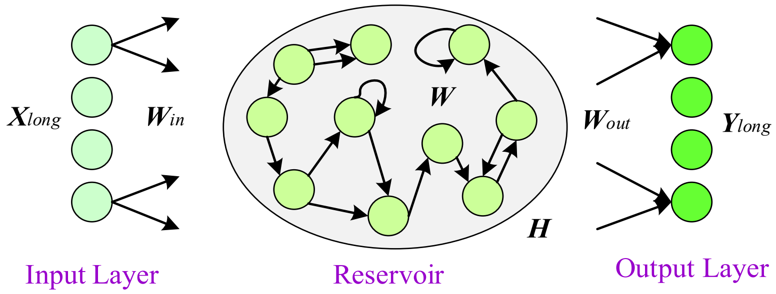


Figure 5. Echo state neural network

The process of ESN algorithm includes two phases: initialisation of weight parameters and training.The ESN network contains a relatively large number of neurons, and the connection weights between neurons in the storage pool are randomly generated and their connections are sparse.The hyperparameters of the ESN affect the prediction effect, and the adjustment of the hyperparameters is very important, in which the ESN hyperparameters include the size of the storage pool N_r , the spectral radius SR , the input scaling factor IS , the sparsity of storage pool . degree SD .

In order to capture the predicted input parameters at multiple scales, this section combines the self-encoder and ESN to propose a self-encoder based Deep Echo State Network (DeepESN).DeepESN is based on the ESN's and increases the number of layers in the reserve pools through the mapping of the self-encoder. In DeepESN network structure, the previous reserve pool echo state is reduced to low dimensions by AE, input to the next reserve pool, and so on to the last layer, collate all the echo states, and output the final result to the network through the output layer.The DeepESN network structure is shown in Figure 6.The mathematical model of DeepESN network is represented as follows:

$$\boldsymbol{H}_{in}^{(l)}(t)=\boldsymbol{W}_{in}^{(l)}\boldsymbol{X}_{in}^{(l)}(t)+\boldsymbol{W}^{(l)}\boldsymbol{H}^{(l)}(t-1) \quad (7)$$

$$\boldsymbol{X}_{in}^{(l)}(t)=\begin{cases}\boldsymbol{X}_{long}(t), l=1\\ f_{enc}\left(\boldsymbol{W}_{enc}^{(l-1)}\boldsymbol{H}^{(l-1)}(t)\right), l>1\end{cases} \quad (8)$$

$$\boldsymbol{H}^{(l)}(t)=\left(1-SD^{(l)}\right)\boldsymbol{H}^{(l)}(t-1)+SD^{(l)}\tanh\left(\boldsymbol{H}_{in}^{(l)}(t)\right) \quad (9)$$

$$\boldsymbol{Y}_{long}(t)=g\left(\boldsymbol{W}_{out}\boldsymbol{H}(t)\right) \quad (10)$$

In the above Eq. (7)-Eq. (10), $\boldsymbol{H}_{in}^{(l)}(t)$ denotes the weighted input data of the storage pool in layer *l at* time *t*, $\boldsymbol{W}_{in}^{(l)}$ denotes the connection weight from the input of layer *l* to the storage pool, $\boldsymbol{X}_{in}^{(l)}(t)$ denotes the input of layer *l at* time *t*, $\boldsymbol{W}^{(l)}$ denotes the feedback weight of the state of the storage pool of layer *l*, $\boldsymbol{H}^{(l)}(t-1)$ denotes the state of the storage pool of layer *l* at time t-1, $\boldsymbol{W}_{enc}^{(l-1)}$ denotes the self-encoder projected weight of layer l-1 at time t, $f_{enc}(\cdot)$ *den*otes the self-encoder activation function, $\boldsymbol{X}_{long}(t)$ denotes the input variable of layer l at time t, denotes the state value of layer l at time t, and denotes the sparsity degree of the storage pool. the input variable at time t, $\boldsymbol{H}^{(l)}(t)$ denotes the storage pool state value of layer *l* at time *t*, and $SD^{(l)}$ is the sparsity degree of the storage pool in layer *l*. $\boldsymbol{H}(t)$ The vector formed by the states of all storage pools is denoted as $\left[\boldsymbol{H}^{(1)}(t),\boldsymbol{H}^{(2)}(t),\cdots,\boldsymbol{H}^{(l)}(t)\right]$; $g(\cdot)$ denotes the activation function of the output layer.

The DeepESN neural network training process generally includes initialising the network, obtaining stored state values, and training the output weights. The computation of the output weights $\boldsymbol{W}_{out}$ remains a regression problem and is generally solved using regularised ridge regression.

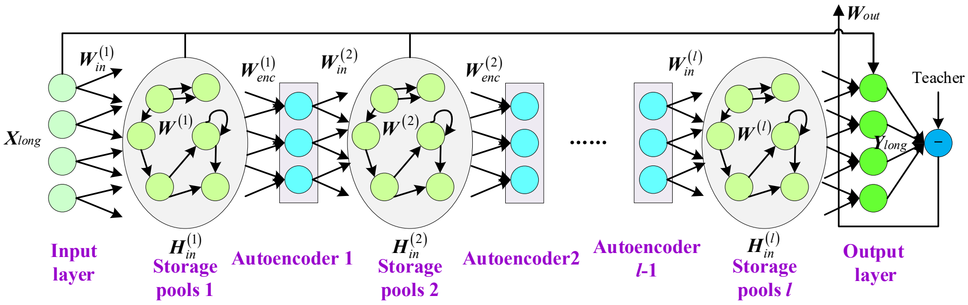


Figure 6. Self-coding based deep echo state network

3.3. Jellyfish optimisation algorithm

Inspired mechanisms

Artificial jellyfish search optimization (JSO) is a bionic optimization algorithm proposed by Chou J S et al. in 2020 [28], which is based on three idealized behavioural rules:

1) Jellyfish either follow ocean currents or move around themselves within a colony, and these two modes of movement are controlled by time-controlled mechanisms;

2) In the ocean, jellyfish search for food and they are more likely to be attracted to locations where there is a large amount of food;

3) The amount of food found is determined by the objective function for that location and the corresponding location.

The movement of a jellyfish in the ocean is shown in Figure 7.

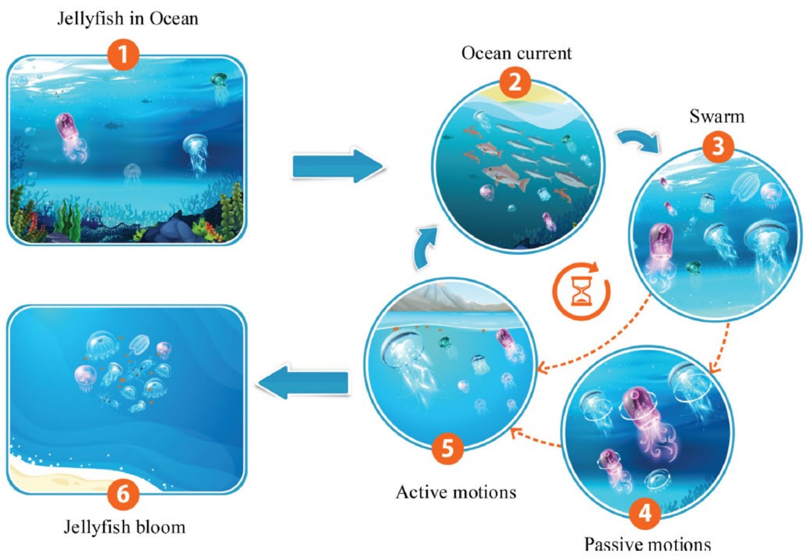


Figure 7. Jellyfish behaviour

Optimisation strategies

1) Population initialisation

Randomly initialised populations are prone to defects such as slower convergence, not being able to jump out of the local optimal solution already poor population diversity. In order to improve the diversity of initialised population, the initial position of jellyfish population adopts Logistic mapping method, and the specific mapping formula is as follows:

$$X_{i+1} = \eta X_i \left(1 - X_i\right) \tag{11}$$

$$0 \le X_0 \le 1 \tag{12}$$

where X_i denotes the logical chaos mapping value of the ith jellyfish position; X_0 is used to generate the initial population, $X_0 \in (0,1)$, $X_0 \notin (0, 0.25, 0.5, 0.75, 1.0)$, $\eta = 0.4$.

2) Ocean current movement strategy

Jellyfish are attracted to current movement because of the large amount of nutrients present in the current movement. The direction of the ocean current is mainly determined by the average of the jellyfish population position and the best position of the jellyfish, and the strategy of the ocean current movement is shown in Figure 8. The specific simulation equation of the ocean current is as follows:

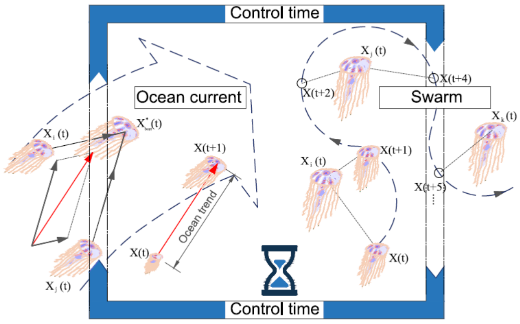


Figure 8. Ocean current movement

$$trend = \frac{1}{n_{pop}} \sum \left(X^* - e_c \mu \right) = X^* - e_c \frac{\sum X_i}{n_{pop}} = X^* - e_c \mu \tag{13}$$

This is known as $df = e_c \mu$:

$$trend = X^* - df \tag{14}$$

where n_{pop} is the number of jellyfish populations, X^* is the best position in the current jellyfish population, e_c is the attractiveness factor, μ is the average position of the population, and df is the difference between the current best position of the jellyfish population and the average of the positions held by all jellyfish.

The jellyfish assumes that the dimensions obey a given normal distribution, and that the $\pm\beta\sigma$ range of mean positions contains all jellyfish possibilities, then:

$$df = \beta \cdot \sigma \cdot rand^f \left(0,1\right) \tag{15}$$

where σ is the standard deviation of the distribution:

$$\sigma = rand^f \left(0,1\right) \tag{16}$$

Based on the calculations at σ , this gives

$$df = \beta \cdot rand^f \left(0,1\right) \cdot \mu \cdot rand^f \left(0,1\right) \tag{17}$$

Simplification of the above equation:

$$df = \beta \cdot rand^f \left(0,1\right) \cdot \mu \tag{18}$$

Let $e_c = \beta \cdot rand\left(0,1\right)$, which gives:

$$trend = X^* - \beta \cdot rand\left(0,1\right) \cdot \mu \tag{19}$$

Jellyfish location updated to:

$$X_i\left(t+1\right) = X_i\left(t\right) + rand\left(0,1\right) \cdot trend \tag{20}$$

assume (office)

$$X_i\left(t+1\right) = X_i\left(t\right) + rand\left(0,1\right) \cdot \left(X^* - \beta \cdot rand\left(0,1\right) \cdot \mu\right) \tag{21}$$

Jellyfish population movement strategies

Jellyfish populations have 2 types of locomotion, passive locomotion (type A) and active locomotion (type B). When the population was first formed, most jellyfish used type A movement, over time, jellyfish increasingly used type B movement. The jellyfish population movement strategy is shown in Figure 9. Type A movement is the movement of jellyfish around their own position, and the corresponding position of each jellyfish is updated as Eq. (22).

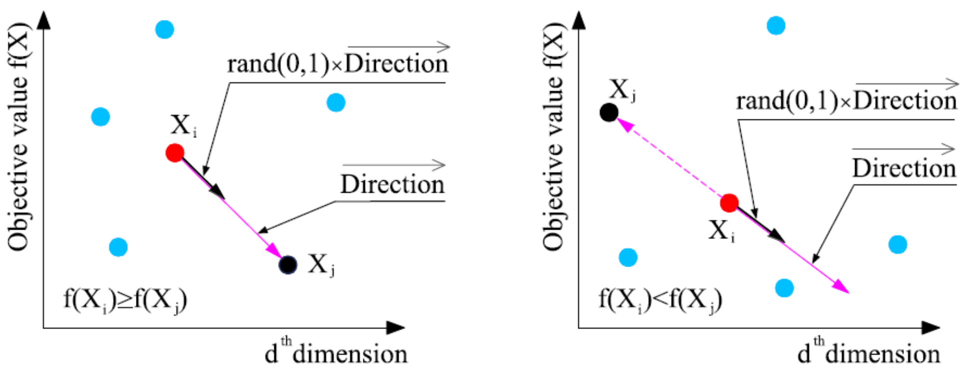


Figure 9. Movement of jellyfish populations

$$X_i(t+1) = X_i(t) + 0.01 \times rand(0,1) \cdot (U_b - L_b) \quad (22)$$

where U_b and L_b denote the upper and lower boundaries of the search space, respectively.

The B-type movement randomly selects 2 jellyfish positions i and j to determine the direction of movement. When the amount of food at position j exceeds the amount of food at position i, the jellyfish at position i moves towards position j, and vice versa, away from it.The equations for the B-movement are given in Eq. (23)-Eq. (25):

$$X_i(t+1) = X_i(t) + Step \quad (23)$$

$$Step = rand(0,1) \times Direction \quad (24)$$

$$Direction = \begin{cases} X_j(t) - X_i(t) & f(X_i) \geq f(X_j) \\ X_i(t) - X_j(t) & f(X_i) < f(X_j) \end{cases} \quad (25)$$

Time control mechanisms

Ocean currents contain large amounts of nutrients that attract jellyfish to move around. Over time, more jellyfish gather in the currents to form jellyfish swarms. When the temperature or wind direction changes the current, jellyfish from the population move into another current and form a new jellyfish colony. To regulate jellyfish current movement and jellyfish intra-population movement, the JSO algorithm uses a time control function $c(t)$ and a constant threshold $c0$, where the time control function is a random value that varies with the number of iterations and takes a value in the range $[0,1]$. $c0$ It is set to 0.5. The time control function with iteration process is shown in Figure 10, and the specific calculation formula is shown in Equation (26):

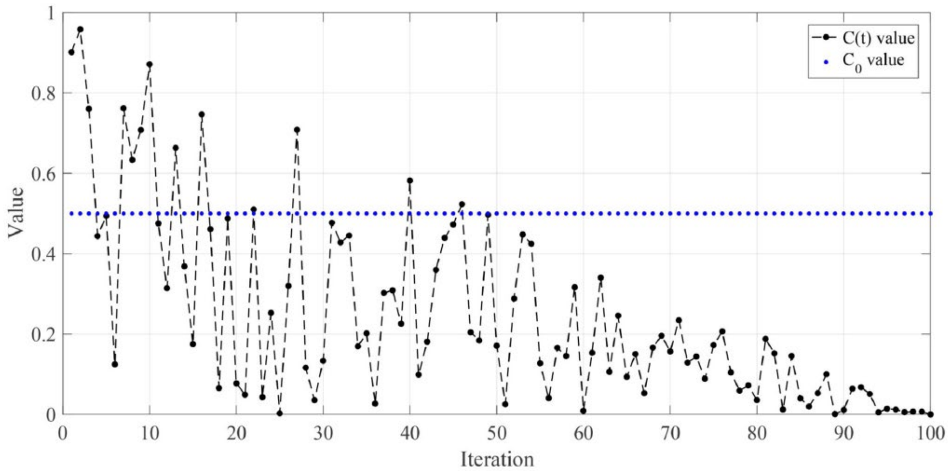


Figure 10. Practical control with iterative process

$$c(t) = \left| \left(1 - \frac{t}{Max_{iter}}\right) \cdot \left(2 \times rand(0,1) - 1\right) \right| \quad (26)$$

Where t denotes the specified number of iterations and Max_{iter} denotes the maximum number of iterations. When $c(t)$ exceeds $c0$, the jellyfish follows the ocean currents; when $c(t)$ is less than $c0$, the jellyfish adopts the jellyfish intra-population motion. In addition, to switch between type A and type B motions, $1-c(t)$ is used to describe the type of jellyfish motion. When $1-c(t)<0.5$, jellyfish follow type B motion; as the number of iterations increases, the value of $c(t)$ changes from 0 to 1, the probability of $1-c(t)<0.5$ gradually decreases, and jellyfish intrapopulation motion tends to be more and more like type A motion.

Strategies for dealing with transgressions

To prevent the jellyfish from moving beyond the search boundary, JSO uses an out-of-bounds processing strategy, i.e:

$$\begin{cases} X'_{i,d} = \left(X_{i,d} - U_{b,d}\right) + L_{b,d} & X_{i,d} > U_{b,d} \\ X'_{i,d} = \left(X_{i,d} - L_{b,d}\right) + U_{b,d} & X_{i,d} < L_{b,d} \end{cases} \tag{27}$$

where $X_{i,d}$ denotes the position of the ith jellyfish in the dth dimension, $X'_{i,d}$ denotes the updated position after checking the boundary constraints, and $U_{b,d}$ and $L_{b,d}$ are the upper and lower bounds in the dth dimension, respectively.

(3) JSO Algorithm Flow

According to the seagull optimisation strategy, the specific steps of the JSO algorithm are as follows:

Step 1: Initialise the population position using Logistic mapping method, set the maximum number of iterations and other parameters;

Step 2: Calculate the fitness value and record the current optimal individual;

Step 3: Calculate the time control function;

Step 4: Jellyfish population position update. If the control parameter is greater than or equal to the threshold value of 0.5, the jellyfish follows the ocean current movement; if the control parameter is less than 0.5, the jellyfish adopts the jellyfish intra-population movement; if $1-c(t)<0.5$, the jellyfish follows the B-type movement; otherwise, it follows the A-type movement; and according to the movement strategy, the new position of the jellyfish population is calculated;

Step 5: Check the boundary conditions, calculate the fitness value and update the optimal individual;

Step 6: Determine whether the number of iterations reaches the maximum number of iterations. If the maximum number of iterations is reached, carry out the output of the optimal solution and optimal value; otherwise, go to step 3.

Algorithm performance analysis

In order to analyse the performance of the JSO algorithm, this paper uses a simple standard function Rastrigin function for testing and analysis, the optimal value of this function is located at $(0,0)$ and the value is 0. Figure 11 gives the iterative population distribution of the SO algorithm. From Figure 11, it can be seen that the population distribution is relatively uniform at the beginning of the iteration; at the 10th iteration, some individuals are close to the optimal value; at the 25th iteration, most individuals are close to the optimal value; at the 50th iteration, most of the individuals converge to the optimal value.

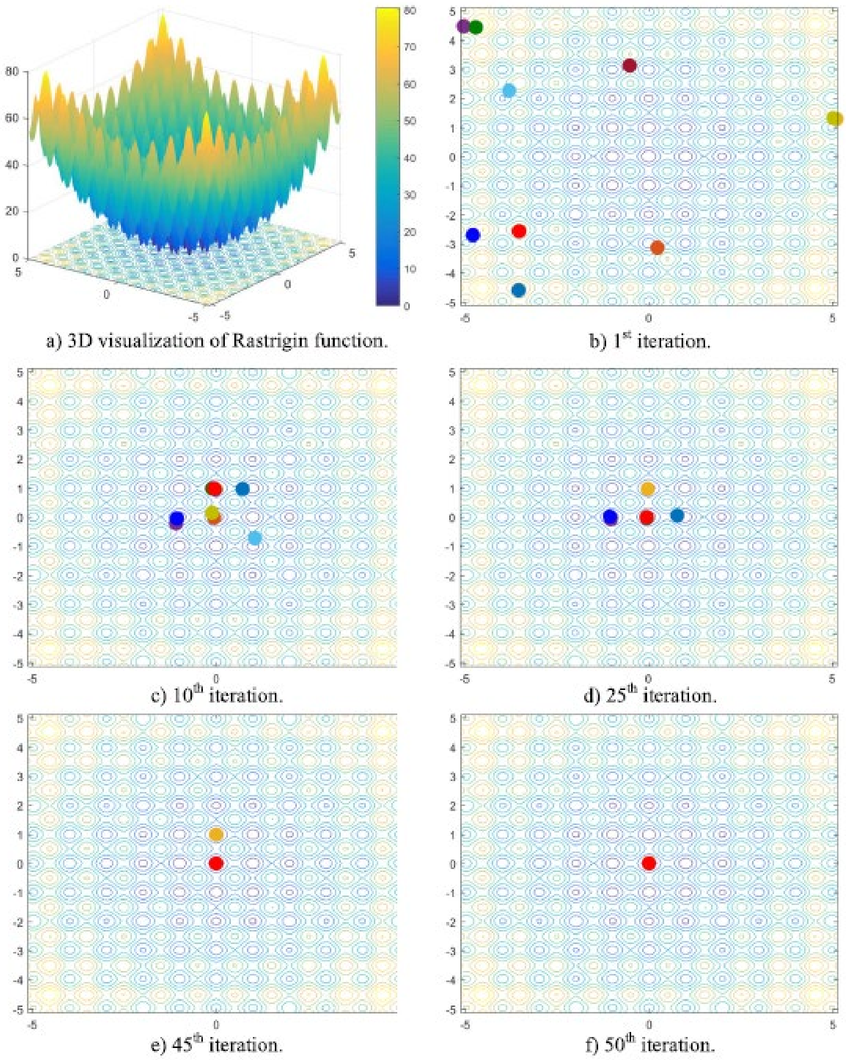


Figure 11. Iterative analysis diagram of JSO algorithm

4. Credit Risk Prediction Process for Combined Blockchain Supply Chain Finance Based on KPCA-JSO-DeepESN Algorithm

4.1. Deep echo state network prediction model based on JSO algorithm

Combining JSO and DeepESN, this section proposes a combined blockchain supply chain finance credit risk prediction method based on JSO algorithm to improve DeepESN network.

Decision variables and objective functions

DeepESN network storage pool size N_r , spectral radius SR , input scale factor IS , and storage pool sparsity SD affect the performance evaluation accuracy. In order to improve the accuracy of credit risk prediction and evaluation in supply chain finance, this paper adopts the JSO algorithm to optimise the DeepESN network storage pool size N_r , the spectral radius SR , the input scale factor IS , and the sparsity degree of the storage pool SD . The optimisation decision variable of the GRO algorithm is $\theta = (N_r, SR, IS, SD)$.

To further DeepESN training accuracy, the root-mean-square error function is used as the objective function of the JSO-DeepESN algorithm, which is calculated as follows:

$$\min f\left(N_r, SR, IS, SD\right)=\sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(y(k)-y_{predict}(k)\right)^2} \tag{28}$$

$y(k)$ is the actual value and $y_{predict}(k)$ is the predicted value.

Steps and Processes

The combined blockchain supply chain financial credit risk prediction and assessment model based on the JSO algorithm optimised DeepESN network mainly takes the prediction and evaluation indicators as inputs and the evaluation value as outputs, and the mapping relationship between the indicators and the evaluation value. The flow chart of the combined blockchain supply chain financial credit risk prediction and evaluation method based on the JSO-DeepESN algorithm is shown in Figure 12. The specific steps are as follows:

Step 1: Acquire data based on the questionnaire method and platform network method; pre-process the acquired samples with sparse smoothing data processing method; normalise the raw data with Z-Score method and divide the data into testing set, validation set and training set;

Step 2: The initial parameters of DeepESN are encoded using the JSO algorithm, and the algorithm parameters such as population parameters, iteration number, etc., are initialised; the population is initialised and the objective function value is calculated;

Step 3: Execute the follow-current-motion, jellyfish-in-population-motion strategy for position updating according to the JSO algorithm optimisation strategy;

Step 4: In each iteration, compare the objective function value of each candidate solution with the objective function value of the current global optimal solution and update the global optimal solution;

Step 5: Judge whether the termination condition is satisfied. If it is satisfied, exit the iteration, output the optimal DeepESN parameters, and execute step 6, otherwise continue to execute step 3;

Step 6: Decode the JSO algorithm based optimised DeepESN parameters for $\theta^* = \left(N_r, SR, IS, SD\right)$;

Step 7: Construct the JSO-DeepESN analysis model, train the analysis model using the training set, input the test set into the model, and obtain the analysis and error results.

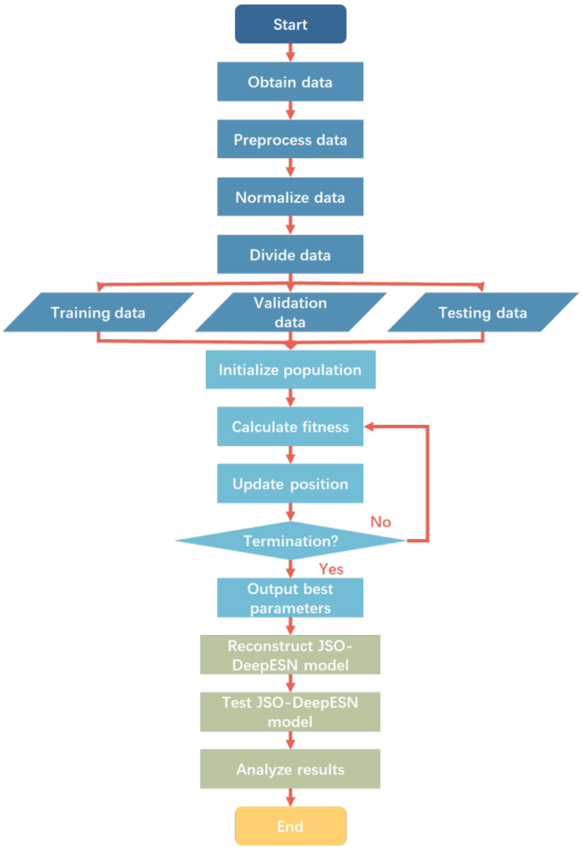


Figure 12. Flowchart of predictive evaluation for optimising DeepESN network based on JSO algorithm

4.2. Steps of credit risk prediction and evaluation process of supply chain finance based on blockchain technology

Combined with KPCA, the JSO-DeepESN prediction method proposed in this paper is applied to the problem of combining blockchain supply chain financial credit risk prediction and assessment, and the main steps are:

Step 1: The kernel principal component analysis method is used to extract features and analyse the credit risk evaluation indicators of supply chain finance;

Step 2: In order to improve the accuracy of the prediction and evaluation model, the JSO algorithm is used to find the optimal DeepESN parameters and select the optimal DeepESN parameters;

Step 3: Analyse the performance of the predictive model proposed in this paper.

5. Results and discussion

In order to verify the accuracy and timeliness of the credit risk prediction and evaluation model of supply chain finance based on blockchain technology proposed in this paper, five prediction and evaluation algorithms are selected for comparison, and the specific parameter settings of each algorithm are shown in Table 1.The data are mainly from the credit risk prediction and evaluation data of automobile manufacturing supply chain finance. The experimental simulation environment is Windows 10, CPU is 2.80GHz, 8GB memory, programming language Matlab2017b.

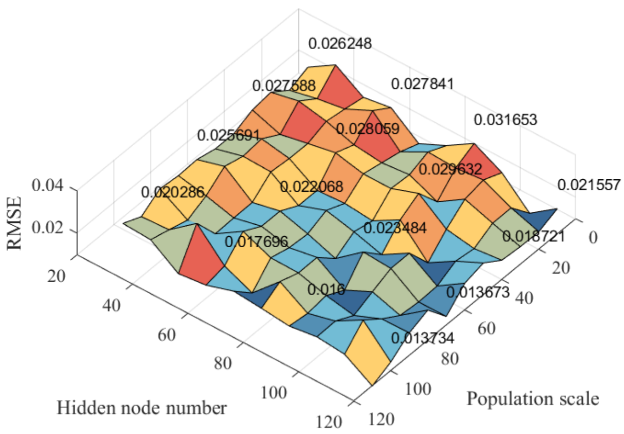
Table 1. Parameter settings of supply chain finance risk prediction and evaluation methods

arithmetic	parameterisation
ESN	sd=0.7, nr=100, sr=0.2, is=0.25
DeepESN	SD=0.7, Nr=100, SR=0.2, IS=0.25, three AE layers, see section 5.2 for reference analysis of the number of nodes in each layer
WOA-DeepESN	DeepESN network with three AE layers, see section 5.1 for reference analysis of the number of nodes in each layer; WOA algorithm a decreasing from 2 to 0, spiral shape parameter 1, see section 5.1 for the number of populations
TSA-DeepESN	DeepESN network three AE layers, see section 5.1 for reference analysis of the number of nodes in each layer; TSA algorithm ST = 0.1, see section 5.1 for the number of populations
SOS-DeepESN	DeepESN network three AE layers, see section 5.1 for reference analysis of the number of nodes in each layer; see section 5.1 for the number of SOS algorithm populations
JSO-DeepESN	DeepESN network three AE layers, see section 5.1 for reference analysis of the number of nodes in each layer; see section 5.1 for the number of JSO algorithm populations

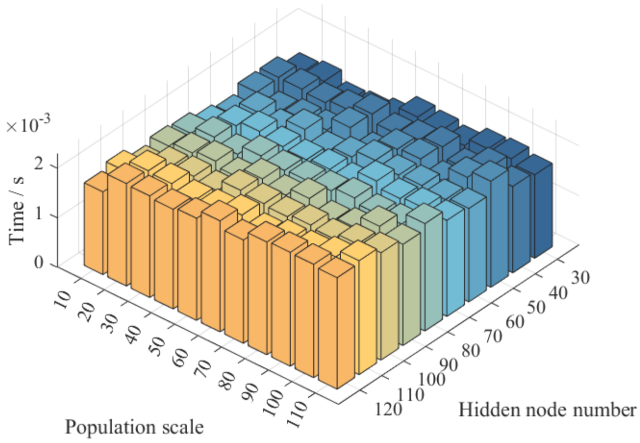
5.1. Parameter setting analysis

In order to obtain the appropriate number of nodes in the AE layer of the DeepESN network and the number of populations of the optimisation algorithm, this section analyses the effect of different population numbers and the number of nodes in the hidden layer on the prediction evaluation value and the prediction evaluation time.

Figure 13 gives the impact of different population numbers and AE layer node numbers on supply chain finance risk prediction evaluation value and prediction time. From Figure 13(a), it can be seen that the prediction accuracy increases as the number of populations increases; the prediction accuracy increases as the number of nodes in the hidden layer increases. From Figure 13(b), it can be seen that the prediction time increases as the number of populations increases; the prediction time increases as the number of AE layer nodes increases. In summary, the increase in the number of populations with the number of nodes in the AE layer of the supply chain financial risk prediction and evaluation model is conducive to the increase in prediction accuracy, but the prediction time increases. In order to balance the contradiction between time and accuracy, the number of populations should be selected as 60 and the number of hidden layer nodes as 100.



(a) Results of the impact on the accuracy of prediction evaluation



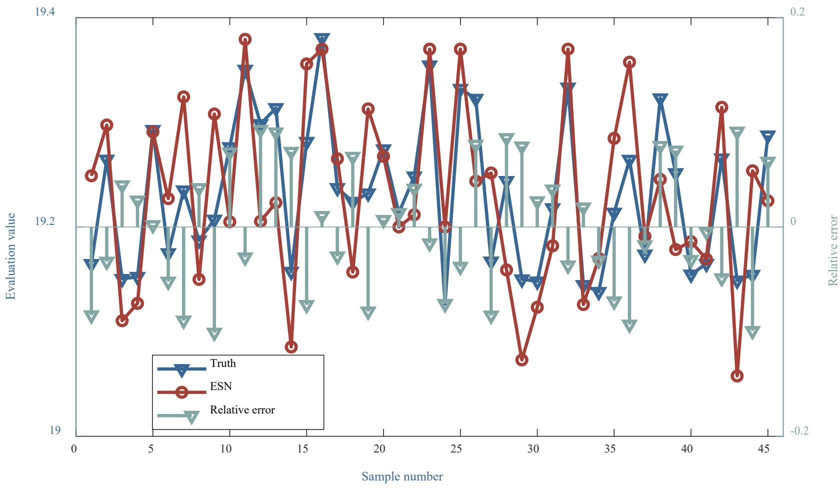
(b) Impact results on predicted evaluation times

Figure 13. Effect of different population size and number of cryptic nodes on predicted evaluation value and predicted evaluation time

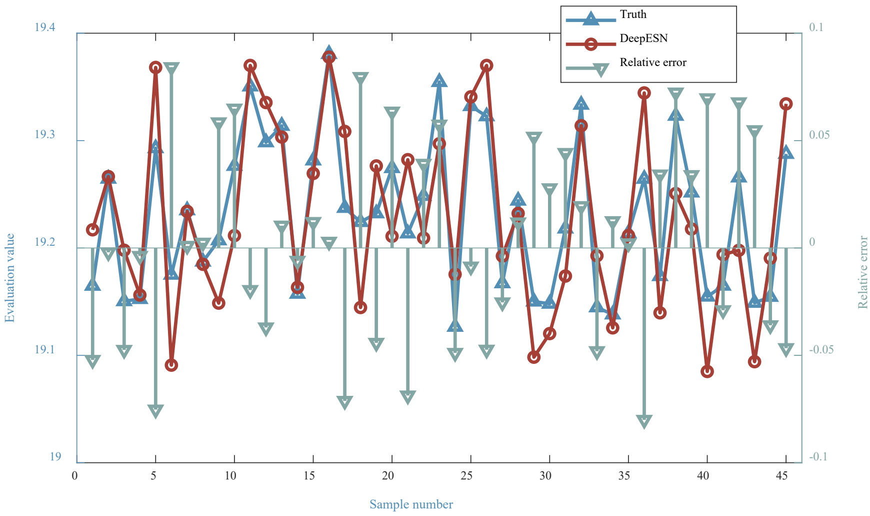
5.2 Experimental analyses

In order to verify the effectiveness and superiority of the supply chain finance risk prediction and evaluation method based on the JSO-DeepESN algorithm, JSO-DeepESN is compared with ESN, DeepESN, WOA-DeepESN, TSA-DeepESN, and SOS-DeepESN, and the evaluation results of each model are shown in Figure 14 and Figure 15.

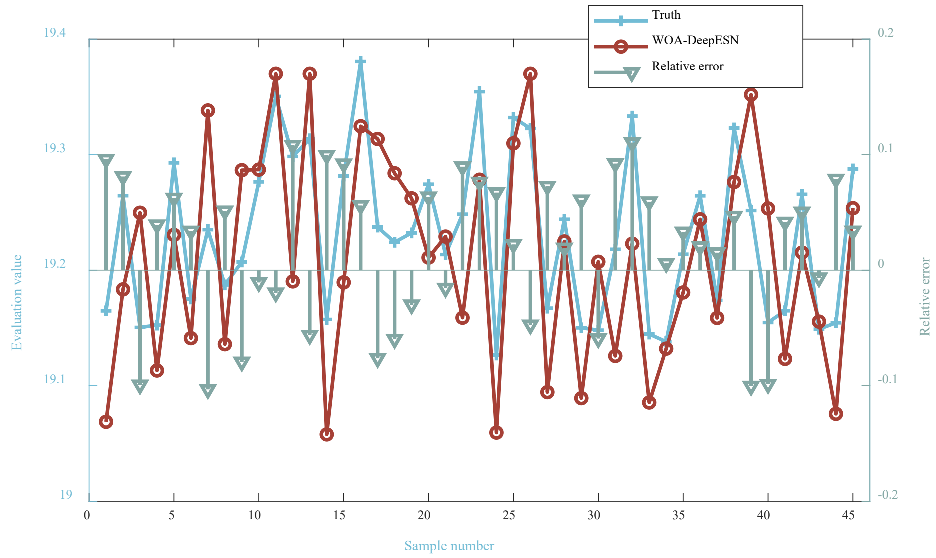
Figure 14 gives the relative error between the supply chain finance risk prediction evaluation value and the true value based on each algorithm. From Figure 14, it can be seen that the supply chain finance risk prediction appraisal value based on JSO-DeepESN is closer to the true value and the relative error is controlled within 0.04; the prediction relative errors of ESN, DeepESN, WOA-DeepESN, TSA-DeepESN, and SOS-DeepESN algorithms are controlled within 0.2, 0.1, 0.12, 0.09, and 0.05 range, respectively. In summary, the error of the supply chain finance risk prediction and evaluation method based on the JSO-DeepESN algorithm is generally minimal.



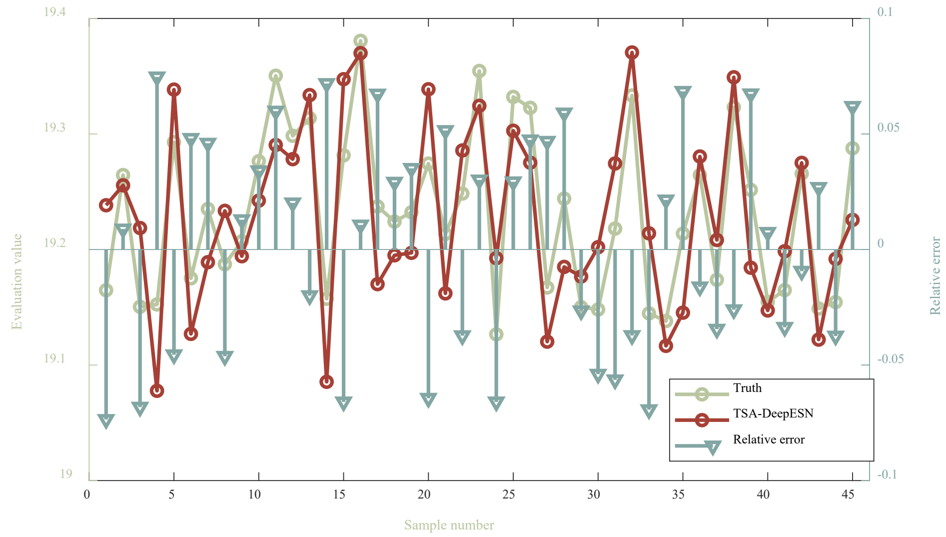
(a) ESN



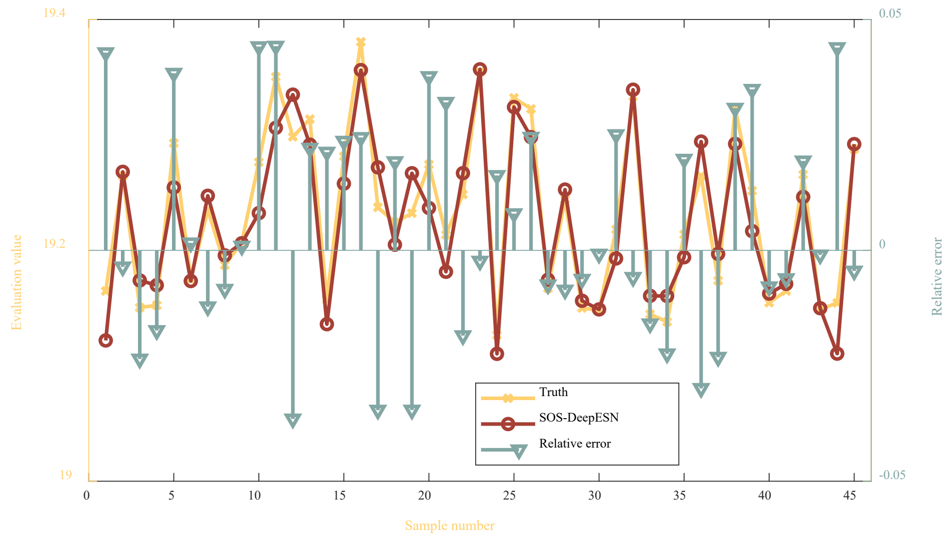
(b) DeepESN



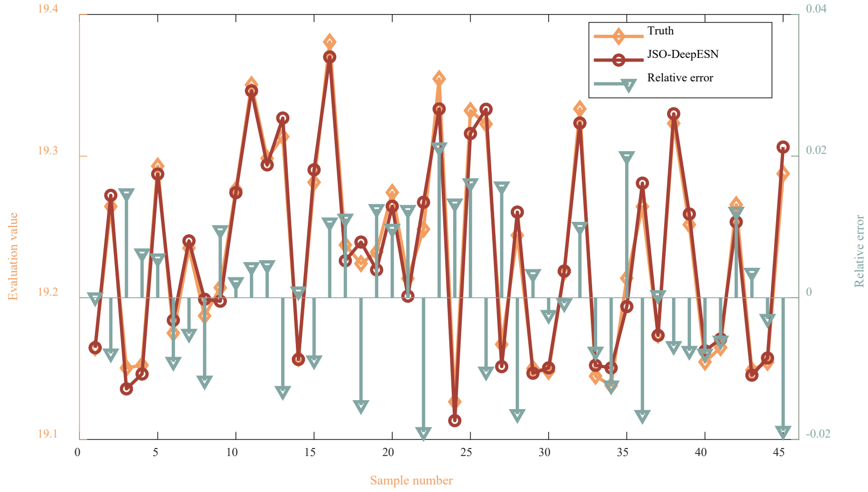
(c) WOA-DeepESN



(d) TSA-DeepESN



(f) SOS-DeepESN



(e) JSO-DeepESN

Figure14. Credit risk prediction value and error results of supply chain finance based on each algorithm

From Figure 15, it can be seen that the prediction time of supply chain financial risk prediction and evaluation methods based on JSO-DeepESN algorithm is better than other algorithms; from the perspective of prediction time mean, the ranking of supply chain financial risk prediction and evaluation methods is JSO-DeepESN, SOS-DeepESN, TSA-DeepESN, WOA-DeepESN in the order of JSO-DeepESN, SOS-DeepESN, TSA-DeepESN, WOA-DeepESN, DeepESN, ESN; from the point of view of the standard deviation of prediction time, the ranking of supply chain financial risk prediction and evaluation methods is JSO-DeepESN, SOS-DeepESN, WOA-DeepESN, TSA-DeepESN, ESN, DeepESN, in order of magnitude.It can be seen that, supply chain financial risk prediction and evaluation methods based on the JSO-DeepESN algorithm prediction and evaluation method performs better than other algorithms, with better prediction accuracy and better real-time performance than other algorithms.

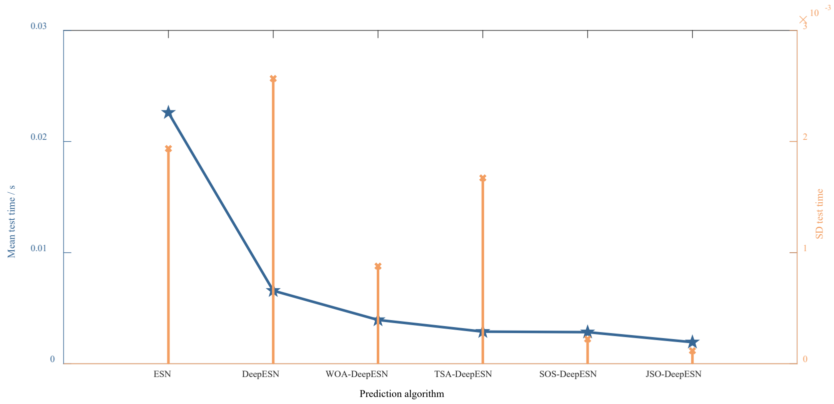


Figure 15. Comparison of evaluation time results of supply chain finance credit risk prediction based on each algorithm

It can be seen that from Figure 16, the optimisation efficiency of credit risk prediction and evaluation of supply chain finance based on JSO-DeepESN algorithm is better than that of SOS-DeepESN, TSA-DeepESN, and WOA-DeepESN; JSO-DeepESN algorithm has the fastest convergence and the best convergence accuracy.

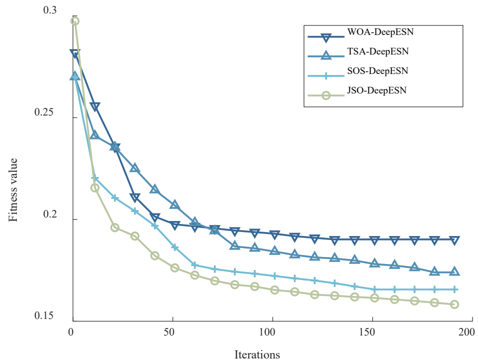


Figure 16. Comparison of DeepESN parameter optimisation curves based on each intelligent optimisation algorithm

6. Conclusion

This paper proposes a combined blockchain supply chain financial credit risk prediction and evaluation method based on KPCA and JSO-DeepESN. The method constructs a supply chain financial credit risk prediction and evaluation model by describing the supply chain financial credit risk prediction and evaluation problem based on blockchain technology, analyzing the evaluation indexes, and constructing the evaluation system; combining with the kernel principal component analysis method and using the JSO algorithm to optimize the DeepESN network parameters. Through experimental analysis, the following conclusions are obtained:

1) By analysing JSO-DeepESN with other methods, it is verified that the proposed algorithm can improve the efficiency of the prediction model;

2) By comparing JSO-DeepESN with SOS-DeepESN, TSA-DeepESN and WOA-DeepESN, it is verified that the JSO algorithm optimises the DeepESN network with faster convergence and better accuracy;

3) The DeepESN model based on JSO optimisation is not only better than other prediction models in terms of prediction accuracy, but also takes less time to predict food prices;

The robustness of the prediction model proposed in this paper is not good, and the JSO algorithm can easily fall into the local optimum, improving the JSO algorithm ahfa optimisation strategy is the next research focus.

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