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Risk model of financial supply chain of Internet of Things enterprises: A research based on convolutional neural network

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ABSTRACT

The emergence of the financial supply chain provides assistance for small, medium and micro enterprises in the supply chain through a secured credit model based on real trade. Moreover, in the multi-level structure of the financial supply chain of the Internet of Things enterprise, there are information barriers and information islands. Besides, data is often not transmitted smoothly, and the intermediate offline process is complicated. What is worse, the efficiency is low, and the verification cost is high. Therefore, based on supply chain finance, an evolutionary risk model is constructed in this paper. Firstly, the income matrix of the regulatory risk model is established, and the convolutional neural network used will pool the training data to the maximum and set the local corresponding normalization layer. With the help of the evolutionary risk theory, the dynamic equation of the financial supply chain is obtained, forming the dynamic path and abnormal model of strategy selection. Then, a compact pattern tree is added to the knowledge granularity method to mine data anomalies. Finally, an experimental platform is built to verify the effectiveness of the method proposed in this paper, and experiments are performed on the accuracy of model evolution conditions, abnormal data identification, and abnormal numerical examples. The experimental results prove that the algorithm in this paper is consistent with the set parameters, and the effect is significantly higher than other comparison methods. The experimental mining time and the comparison method are shortened by 6∼13S. The research results obtained from this paper solve the problem that the decision-making of supply chain finance and the supervision and review of supply chain enterprise are complex, which improves the characteristics identification of supply chain platform, and provides reference suggestions for financial institutions and supply chain platforms.

1. Introduction

As the development scale of the Internet of Things expands, the economic development of Internet of Things enterprises face many challenges like the great downward pressure on the economy. The development of corporate financial supply chains is becoming more and more important. However, there are many problems that need to be solved in the traditional corporate financial supply chain. For example, the high-quality credit of core enterprises has not been fully utilized, causing a lot of financial expenses. Small and medium-sized enterprises are of insufficient credit qualifications, so that the financing needs of enterprises will be large. Meanwhile, the bargaining power of the industry chain is weak, with many sales on credit. In addition, enterprises cannot maintain the continuous growth of the financing scale only with the help of their own funds. Moreover, the traditional credit model cannot meet the requirements of upstream and downstream enterprises in the supply chain [1]. At this time, the rapid development of corporate financial supply chain can just solve the problem appearing in traditional corporate financial supply chain. As a component of the technology industry, the corporate financial supply chain includes block-chain, big data, artificial intelligence, the Internet of Things, cloud computing and other technologies, which can be widely used in various industries to improve the efficiency empowering the real economy, reduce the cost serving the real economy, and prevent and control the risk serving the real economy to a great extent [2].

The corporate financing has always been focused. From bank loans to P2P, it solves the financing needs of some enterprises and individuals. However, a large quantity of small, medium and micro enterprises cannot obtain loans due to insufficient qualifications and credit certificates as well as property certificates. What is worse, there are a lot of credit risks and social problems in the loan process [3]. Even if core companies provide guarantees, new problems such as slow information, high costs, and risk of fraudulent loans have arisen. Information cannot be transparent, and simple credit guarantees cannot truly represent the credit of small, medium and micro enterprises. The model "Internet + supply chain" is difficult to follow up the flow of funds and information timely, and small, medium and micro enterprises

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may have mismanagement or breach of contract. Even core enterprises may forge transaction information to cheat loans [4].

Financial supply chain is different from traditional credit. Compared with the traditional credit, the credit requirements of the enterprises in the supply chain of banks and other financial institutions are not so high, but separate the transaction paths on the chain for separate credit [5]. In other words, the financial supply chain only provides credit financing for the creditor's rights and goods rights of the enterprises in the chain. It is mainly manifested in several aspects: first, it is closely related to goods trading; second, the use of funds is deterministic; third, it requires dynamic supervision of the use of funds. Therefore, under the mode of financial supply chain, the debt repayment fund has the characteristics of "closed and self compensation". The guarantee of self compensation comes from the effective control of the trade under the financing, and the closed protection comes from the integration of the upstream and downstream of the industrial chain and the dynamic monitoring of the capital [6].

The current mainstream model of financial supply chain, namely "M+1+N", in which "1" represents new fintech, "M" and "N" both represent upstream and downstream enterprises, indicating that the supply chain system has been decentralized. The underlying data collection and analysis to be more perfect, can create more financial scenarios, financial supply chain services penetrated down, with different preference of financing enterprises realize seamless docking, capital turnover is good, but, this kind of model of technology demand is higher, need to financial institutions, technology companies, such as multilateral cooperation, to complete the construction [7]. The model of "block chain + financial supply chain" belongs to this model, which is a milestone achievement of new science and technology in the traditional financial field. Under the policy background of combining industry and finance and getting rid of the imaginary to the real, the financial supply chain takes serving the real economy as its instinct to promote the better and faster development of the real economy [8].

Domestic and overseas scholars have conducted a lot of research on the definition and importance of the financial supply chain. Berger and Udell [9] put forward a complete framework for SME financing, elaborating the idea of "government policy-financial structure-loan technology" to solve the problem of SME financing. The supply chain financing is one of the important technical means. Moreover, Michael [10] redefined the concept of financial supply chain based on previous studies. It is believed that the financial supply chain is a process of systematically optimizing the availability and cost of funds in a corporate ecosystem dominated by core companies. Li Yixue et al. [11] defined the concept of logistics finance. In other words, financial institutions cooperate with logistics companies to provide customers with settlement, financing, insurance and other related services during the operation of the supply chain. The core of the business is logistics financing. In a narrow sense, logistics finance refers to logistics financing. Besides, Cheng Haoliang [12] pointed out that information technology can provide important support to the financial supply chain in terms of business support, risk management and control, and channel expansion, explaining the basic concepts, technical requirements, functional requirements and implementation plans of financial supply chain informatization, and summarizing the main problems existing in the development of financial supply chain informatization in China. Meanwhile, corresponding development suggestions are put forward. Guillen et al. [13] and William [14] believed that financial supply chain management can help companies in the supply chain ecosystem dominated by core companies to reduce costs and transfer risks. More research attentions are paid on the combination of the Internet and finance, lacking the practical application of supply chain finance. Research is partial to the macro adjustment of the supply chain, without making recommendations from the supply chain itself.

Existing theoretical research is discussed from the traditional supply chain financial model construction and risk control, and there are few researches on the introduction of new information technology or financial technology. Moreover, existing game studies examine the equilibrium solutions and optimal decisions of various decision-making parties in the traditional supply chain finance process, and there are few evolutionary game studies that deeply explore the multi-party evolution process of supply chain finance. The existing researches on blockchain technology combined with supply chain finance are mostly pure theoretical analysis and prospects. In addition, existing game research examines the evolutionary game model of traditional supply chain finance and adds relevant parameters of the blockchain to this model, establishing an evolutionary game model of supply chain finance under the application of block-chain. The evolutionary decisions of supply chain enterprises and financial institutions are obtained by solving the model. Therefore, the paper has certain theoretical significance.

This paper focuses on abnormal mining of corporate financial supply chain data risks, and summarizes some special patterns in financial data through analysis. These rules can quickly detect data in the supply chain, but this process needs to be completed manually, resulting in low precision and efficiency of abnormal data mining. At the same time, there are many biases in the method. Based on personal assumptions and intuition, attention is paid to the detection of data in the supply chain, and rules are used to search for some possible abnormal data points, and then detailed discrimination is made. This kind of manual operation method is of poor objective and real-time performance, and the process is complicated and prone to errors. Besides, since there are too many levels of data in the corporate financial supply chain, this kind of abnormal data mining requires a high cost of manpower and material resources. However, the traditional mining methods based on statistics, distance, density, and clustering are difficult to meet the real-time needs of enterprise financial supply chains. Therefore, based on the participation of convolutional neural network technology, the specific path of the evolution of supply chain finance is studied in this paper. By constructing the payment game matrix between core enterprises and small and medium-sized enterprises, the enterprise financial supply chain risk evolution model is established for numerical example analysis. Moreover, on the basis of the above model, compared with the traditional supply chain finance model, it is verified by numerical simulation and proved that the accuracy and precision of the algorithm in this paper have been significantly improved.

The innovations of this paper are:

An evolutionary game model based on supply chain finance is constructed. Based on the cooperation mode between supply chain financial decision-making parties and the supervision and review of supply chain enterprises by financial institutions, a cooperative evolutionary game model and a supervisory evolutionary game model are respectively established in the paper.

Based on the knowledge granularity method, a compact pattern tree is added as a method for secondary data anomaly mining.

The characteristics of blockchain technology are combined in the model. The relevant parameters of block-chain technology is introduced to modify and recalculate the model, obtaining a new evolution path and balanced and stable decision-making.

Organizational structure of this paper is as follow.

Section 1 introduces the background and research significance of the topic selected in this paper. Section 2 is about the overview of related work. Section 3 is about the enterprise financial supply chain model based on the Internet of Things. Section 4 is about the evolutionary risk anomaly analysis. Section 5 is about enterprise data anomaly mining and simulation experiment analysis. Section 6 summarizes and looks forward to the full text.

2. Related work

Related technologies are introduced in this paper from several aspects of enterprise risk assessment, convolutional neural networks and transfer learning training strategies.

2.1. Corporate risk assessment

In the process of risk assessment and access control, multiple dimensions of risk events and multiple influencing factors are analyzed and judged on the security of information in the process of access request. At the same time, it interacts with the access control strategy to ensure that the risk impact is acceptable. Then, the best control strategy is assigned under the previous problem [15].

The first step in the risk assessment process is risk assessment preparation, which is planned for the entire risk assessment, and there are steps in the assessment process in stages. It is mainly to grasp the overall situation before carrying out the risk assessment steps, including the understanding of the assessment object and the determination of the final assessment target, as well as clear assessment tasks and the establishment of a scientific risk assessment process.

The identification of risk factors is to restrict the access authority of access control to the scope of the access control object, so that the computer system can be used within the scope of authority. Therefore, in risk assessment, the dynamic analysis of each attribute in the access control process is the focus of identifying risk factors.

The risk determination is based on the risk evaluation indicators constituted by the identified risk factors to establish a risk evaluation system and obtain the relevant factors that affect authorization during the access control process. Then, a set of scientific and reasonable risk level judgment rules are formulated based on relevant specifications and existing evaluation methods. Moreover, the risk assessment factors are based on the judgment rules to obtain the risk of the access control system being evaluated.

According to the evaluation results obtained by the judgment and calculation in the previous process, the risk evaluation conducts a targeted, comprehensive and scientific evaluation of the evaluated object.

2.2. Convolutional neural network

Convolutional neural networks belonging to the category of deep neural networks are composed of multiple convolutional layers, pooling layers, fully connected layers, and classifiers inspired by biological neural structures, and convolutional neural network is a digital simulation of biological visual cognition mechanism and process [16]. Moreover, the convolutional layer is to extract feature, and the purpose of the pooling layer lies in the high-level abstract expression of features, ultimately mining and understanding the high-level features in the image. Different from the structure of traditional machine learning models, convolutional neural networks usually have a merged layer after each convolutional layer, and multiple merged layers together form a feature extractor. Besides, advanced feature extraction can be achieved by stacking multiple convolutional pool structures. However, the output result of the convolutional pool is a two-dimensional feature map, and such complex, highly abstract high-level features cannot be directly input into the traditional classifier [17]. Therefore, the output result of the last pooling layer, namely the features extracted by the convolutional pooling structure is converted into a multi-layer fully connected network structure to realize the mapping and optimization from two-dimensional features to one-dimensional features. Finally, the one-dimensional features output by the fully connected layer will be input to the classifier to obtain the final classification result.

2.2.1. Pooling layer

After extracting features in the convolutional layer, the output feature map will be passed to the pooling layer for further feature selection and information filtering. What is more, the pooling layer contains a pre-configured pooling function, which use the statistical information of the feature map in the adjacent area to replace the result of a single point in the feature map. In addition, the pooling layer generally selects the pooling area with the same size as the convolution kernel scanning function map area, and the pooling process is controlled by the pooling size, step size and filling [18].

2.2.2. Fully connected layer and output layer

The function of the fully connected layer contained in the convolutional neural network is equivalent to the hidden layer in the traditional feedforward neural network. As the last part of the hidden layer in the convolutional neural network, the function of the fully connected layer is to send information to other connected layers. Meanwhile, the feature map loses the spatial topology of the fully connected layer and expands to a vector, thus passing the activation function [19].

From the perspective of characterization learning, the convolution and pooling layers of the convolutional neural network can extract input data, and the function of the fully connected layer is to output a nonlinear combination of the extracted features, which aims to acquire the layer itself without expecting to be able to extract functions but trying to use the existing higher-order functions to achieve the learning goals. In addition, the upper layer of the output layer of a convolutional neural network is often a fully connected layer. Therefore, the structure and working principle of the fully connected layer are the same as the output layer of a traditional feedforward neural network [20]. When faced with an image classification problem, the output layer uses a logistic function or a normalized exponential function (such as a softmax function) to output a classification label to the classification object. When faced with the problem of target recognition, the output content is usually designed as the center coordinates, size and classification label of the output object. When faced with the problem of image semantic segmentation, the output result of the output layer is the classification label of each pixel [21].

2.3. Transfer learning training strategy

In deep learning, to save computing resources and improve computing efficiency, pre-trained models are generally used as the starting point of new models for computer vision and natural language processing tasks, which is called migration learning strategies. In general, these pre-trained models spend a lot of time developing neural networks, so that computing resources and transfer learning can transfer the rich knowledge learned to the problems that need to be studied, thereby saving computing resources [22].

In the transfer learning strategy, the existing knowledge is called the source domain, and the new knowledge learned is called the target domain. The main task of transfer learning is to learn how to transfer knowledge from the source domain to the target domain. Especially in the field of machine learning, transfer learning explores how to apply existing models to new and different but related fields. If traditional machine learning deals with tasks such as model data distribution, annotation and output modification, the model will be not flexible enough and the results will be not good enough, while transfer learning can avoid the shortcomings of traditional machine learning [23]. Moreover, under the constantly changing conditions of data distribution, feature size and model output, it is necessary to organically use the knowledge of the source domain to better model the target domain. In addition, without the help of the calibration data, transfer learning can successfully use the calibration data of the relevant fields to complete data calibration. In other words, the difference between transfer learning and traditional machine learning is that traditional machine learning will establish different models according to different learning tasks, while transfer learning uses data from the source domain to transfer knowledge to the target domain, more quickly establishing the model [24].

Transfer learning can generally be divided into sample-based, feature-based, model-based and relationship-based transfer. Sample-based transfer learning usually completes knowledge transfer by weighting the use of adjusted samples in the source domain. Moreover, function-based transfer learning maps the source domain and target domain to the same space, thereby minimizing the distance between the source domain and the target domain and completing knowledge transfer. In model-based transfer learning, the source domain model and the

Table 1
Regulatory Game Model Parameters under Blockchain Application.

Parameter classification	Parameter symbol	Parameter meaning
Regulatory Game	R_1	Supply chain companies' trustworthy accounts receivable
	R_2	Supply chain companies falsify accounts receivable
	V	The positive effects of supply chain companies' trustworthiness
	b_2	Additional investment yield
	b_3	Financial institution loan interest rate
	c_3	Financial institutions strictly review costs
	c_4	Financial institutions relax audit costs
	c_5	Financial institutions scrutinize the cost of exposing default
	c_6	Loosen review of financial institutions exposes default costs
Docking blockchain technology platform	C	Information reporting cost
	G_1	Block incentive
	P	Penalties for default of core companies under the blockchain
	p_1	core enterprise default penalty (forgery)
	p_2	Punishment for core enterprise breach of contract (not forged)
	H	Financial institutions provide preferential subsidies
	λ	The proportion of forged accounts of core companies

Table 2
Supply chain financial supervision game income matrix under the application of block chain.

Regulatory Game under Blockchain Application	Financial Institutions		
		Request to dock with blockchain platform y_4	Does not require docking with blockchain platform $1-y_4$
Core business	Repayment x_4	$R_1b_2+v+H+G_1-C,\ R_1b_3-C-H$	$\lambda R_2b_2+(1-\lambda)R_1b_2+v,$ $\lambda(aR_2b_3-c_3)+(1-\lambda)(aR_1b_3-c_4)$
	No repayment $1-x_4$	$R_1(1+b_2)-C-p+H,\ p-C-H$	$\lambda\left[R_2(1+b_2)-p_1\right]+(1-\lambda)\left[R_1(1+b_2)-p_2\right],$ $\lambda(p_1-c_3-c_5)+(1-\lambda)(p_2-c_4-c_6)$

target domain model usually need to be combined with the sample to adjusting model parameters. Additionally, relationship-based transfer learning involves learning the concepts between source domains and creating a relationship that makes the source domain similar to the target domain to transfer knowledge [25].

3. Enterprise financial supply chain model based on Internet of things

This paper sets enterprises and financial institutions as decision-makers of the financial supply chain of the Internet of Things, and makes decisions based on their own utility maximization. In the supply chain risk model, the application platform of supply chain risk is introduced. When the supply chain platform is connected, due to the authenticity and transparency of the transaction, the enterprise cannot forge receivables, all of which are real receivables, R_1; if the supply chain platform is not connected, the enterprise will forge accounts at the level of proportion, which will be $R_1\left(1+b_2\right)-C-p+H$. The higher the proportion is, the easier it will be found by financial institutions. In this case, the greater the risk of strict audit by financial institutions will be. When financial institutions require enterprises to connect with the supply chain platform, the pledge of accounts receivable will be canceled as a, and both parties will generate information reporting cost C. The trustworthy repayment of enterprises will bring good social benefits due to their reputation, and they will also get preferential subsidies from financial institutions, which will be recorded as H, and they will get the block incentive G_1 of the supply chain. If an enterprise defaults, it will be fined if it chooses not to repay. The penalty for default after connecting with the supply chain is p. If the supply chain is not connected, the penalty is p_1 for forgery and p_2 for non forgery. A financial institution gets either p_1 or $p-C-H$. When financial institutions conduct strict audit, the cost is c_3, the cost of exposing enterprises' dishonest behaviors is c_5, the cost of financial institutions choose to relax audit is $\lambda\left[R_2\left(1+b_2\right)-p_1\right]+(1-\lambda)\left[R_1\left(1+b_2\right)-p_2\right]$, and the cost of exposing enterprises' dishonest behaviors is $c_6(c_5>c_6)$. The above parameters are shown in Table 1.

According to the above conditions, the income matrix of the regulatory risk model is obtained in this paper, as shown in Table 2.

In Table 2, the proportion that the enterprise chooses to repay at time t is x_4, and the proportion that does not repay is $1\text{-}x_4$. At time t, the proportion required by financial institutions to be connected to the supply chain platform is y_4, and the proportion not required to be connected is $1\text{-}y_4$.

The convolution mechanism of the Internet of things is shown in Fig. 1 [26].

The structure of the Internet of things uses 5×5 kemel and length = L in convolution, and uses the maximum pooling of 2×2 step size of 2 × 2 for each pooling. The conclusion in the regulatory risk model is adopted, and no local corresponding normalization layer (LRN) is set in the structure. This paper includes 7 layers of convolution layer and 2 layers of fully connected layer, with a total of about 130000 parameters to be trained.

4. Evolution risk anomaly analysis

The main problem of risk anomaly analysis application access control is to support the necessary flexibility and scalability of a large number of users and resources in a dynamic and heterogeneous environment, as well as the requirements for collaboration and information sharing. The traditional access control model cannot safely manage cloud resources, and the cloud server does not have the right to access the content of the outsourced data to protect the confidentiality of the data. In addition, traditional access control does not consider uncertainty and risk, making it difficult for RBAC to adapt to the dynamic characteristics of the cloud environment. Therefore, it is an effective method to solve the dynamics in the cloud that extends the risk assessment to the access control model based on the XACML standard [27].

4.1. Evolutionary equilibrium point

According to the income layer in Table 2, the expected income of different decisions of the enterprise is calculated and its comprehensive expectation is obtained:

$$E_{x_4}=y_4(R_1b_2+v+H+G_1-C)+(1-y_4)[\lambda R_2b_2+(1-\lambda)R_1b_2+v] \quad (1)$$

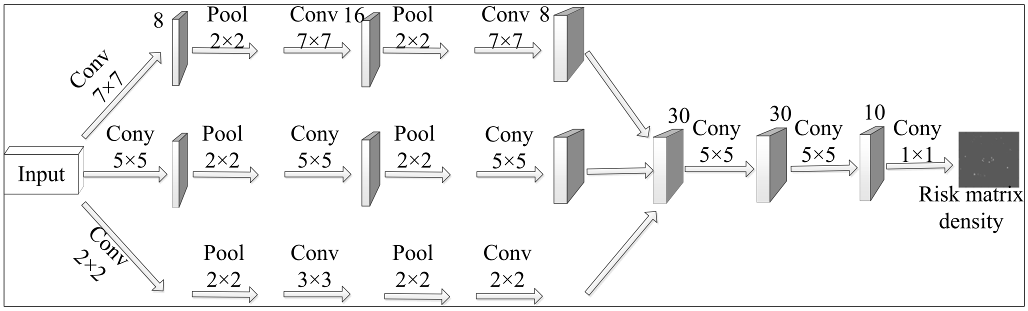

Fig. 1. The convolution structure of the Internet of Things financial risk model.

$$E_{1-x_4} = y_4[R_1(1+b_2) - C - p + H](R_1 b_2 + v + H + G_1 - C) + (1-y_4)\{\lambda[R_2(1+b_2) - p_1] + (1+\lambda)[R_1(1+b_2) - p_2]\} \tag{2}$$

$$\bar{E}_{x_4} = x_4 E_{x_4} + (1-x_4)E_{1-x_4} \tag{3}$$

Calculate the expected earnings of financial institutions when they make different decisions and get their comprehensive expectations:

$$E_{y_4} = x_4(R_1 b_3 - C - H) + (1-x_4)(p - C - H) \tag{4}$$

$$E_{1-y_4} = x_4[\lambda(aR_2 b_3) - c_3 + (1-\lambda)(aR_1 b_3 - c_4)] \tag{5}$$

$$\bar{E}_{y_4} = y_4 E_{y_4}(1-y_4)E_{1-y_4} \tag{6}$$

According to the evolutionary risk theory and the above results, the dynamic equations of enterprises and financial institutions are obtained:

$$F(x_4) = \frac{dx_4}{dt} = x_4(E_{x_4} - \bar{E}_{x_4}) \tag{7}$$

$$F(y_4) = \frac{dy_4}{dt} = y_4(E_{y_4} - \bar{E}_{y_4}) \tag{8}$$

The dynamic equations of enterprises and financial institutions are as follows:

$$A = \lambda R_2 + (1-\lambda)R_1 - \lambda p_1 - (1-\lambda)p_2 - v \tag{9}$$

$$b = G1 + p + \lambda R_2 - \lambda R_1 - \lambda p_1 - (1-\lambda)p_2 \tag{10}$$

$$U = \lambda p_1 + (1-\lambda)p_2 - \lambda(c_3 - c_5) - (1-\lambda)(c_4 + c_6) - p + C + H \tag{11}$$

$$V = R_1 b_3 - p - \lambda aR_2 b_3 - (1-\lambda)aR_1 b_3 + \lambda p_1 + (1-\lambda)P_2 - \lambda c_5 - (1-\lambda)c_6 \tag{12}$$

The following two-dimensional dynamic system is obtained:

$$\begin{cases} \dfrac{dx_4}{dt} = x_4(1-x_4)(B_{y_4} - A) \\ \dfrac{dy_4}{dt} = y_4(1-y_4)(V_{x_4} - U) \end{cases} \tag{13}$$

The whole regulatory risk model is represented by the above two-dimensional dynamic system.

Dynamic paths and anomaly models for strategic choice of enterprises and financial institutions:

Model 1

The equilibrium point of system S_4 is (0,0), (0,1), (1,0) and (1,1). When $0 < \frac{A}{B} < 1$ and $0 < \frac{U}{V} < 1$ are established, (x_4^*, y_4^*) is also the equilibrium point of system S_4, where B and V symbols are unknown, which needs further discussion in different situations. When $B > 0$:

$$\begin{cases} B < 0 \\ A < 0 \\ A - B > 0 \end{cases} \tag{14}$$

When $B < 0$

$$\begin{cases} V < 0 \\ A < 0 \\ A - B > 0 \end{cases} \tag{15}$$

When $V > 0$

$$\begin{cases} V > 0 \\ U > 0 \\ U - V < 0 \end{cases} \tag{16}$$

When $V < 0$

$$\begin{cases} V < 0 \\ U < 0 \\ U - V > 0 \end{cases} \tag{17}$$

4.2. Stability analysis of equilibrium point

Find the Jacobian matrix J_4 of system S_4:

$$x = x^* \tag{18}$$

Of which

$$\left(x_4^*, y_4^*\right) \tag{19}$$

$$\times \tag{20}$$

$$\frac{\partial F(y_4)}{\partial x_4} = \sum y_4(1-y_4)V \tag{21}$$

$$\frac{\partial F(y_4)}{\partial y_4} = \sum (1-2y_4)(V_{x_4} - U) \tag{22}$$

Based on Jacobian Matrix J_4, the dynamic change process of decision-making selection of enterprises and financial institutions is analyzed and studied, and the following Model 2 and 3 are obtained.

Model 2

In the regulatory risk model applied in the supply chain, the B symbol is not determined.

When $B > 0$: if $y = y^*$, the enterprise does not change the original decision; if $y > y^*$, the enterprise will choose not to repay; if $y < y^*$, the enterprise will choose to repay.

When $B < 0$: if $y = y^*$, the enterprise does not change the original decision; if $y > 1$, the enterprise will choose not to repay; if $y < y^*$, the enterprise will choose to repay.

In the regulatory risk model of supply chain application, the V symbol is not determined:

When $V > 0$: if $y = y^*$ and $x = x^*$, SMEs will not change the initial decision; When $x < x^*$, SMEs will choose to default; When $x > x^*$, SMEs will choose to keep faith.

When $y = y^*$: if $y = y^*$ and $x = x^*$, SMEs will not change the initial decision; if $x < x^*$, small and micro enterprises will choose to keep faith; if $x > x^*$, SMEs will choose to default.

Table 3
Results of regulatory risk equilibrium point under supply chain.

Equilibrium point	Index	(0,0)	(0,1)	(1,0)	(1,1)	(x_4^*, y_4^*)
Condition 1	trJ	−	+	−	+	0
	detJ	+	+	+	+	
	Evolution result	ESS	×	×	ESS	Saddle point
Condition 2	trJ	−	−	−	−	0
	detJ	−	−	−	−	×
	Evolution result	×	×	×	×	Saddle point
Condition 3	trJ	−	−	−	−	0
	detJ	−	−	−	−	
	Evolution result	×	×	×	×	Saddle point
Condition 4	trJ	+	−	−	+	×
	detJ	+	+	+	+	
	Evolution result	×	ESS	ESS	×	Saddle point

Evolutionary game model: core enterprises choose repayment and small, medium and micro enterprises choose trustworthiness; core enterprises choose not to repay, and small, medium-sized and micro enterprises choose not to keep their promises.

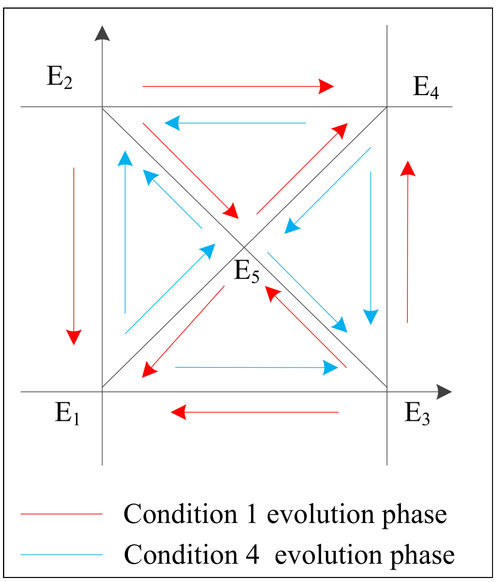

Fig. 2. Phase diagram of regulatory risk evolution under supply chain applications.

According to the stability criterion of the second-order equation and the stability conditions satisfied by the equilibrium points, the above five equilibrium points are substituted into the judgment conditions, and the conditions are calculated as follows:

When $B > 0$ and $V > 0$, it is denoted as condition 1; if $B > 0$ and $V < 0$, it is denoted as condition 2; if $B < 0$ and $V > 0$, it is denoted as condition 3; if $B > 0$ and $V < 0$, it is denoted by condition 4. The results are shown in Table 3:

Table 3 shows that under condition 1, (repayment, required docking) and (non-repayment, not required docking) are evolutionary stabilization strategies. Under the condition of 4 V, (repayment, no docking required) and (non-repayment, no docking required) are evolutionary stability strategies.

Fig. 2 shows the case where there are five equilibrium points, among which E5(X1, Y1) is the saddle point. At this time, there are two evolutionary stability decisions in the cooperative

4.3. Evolutionary analysis

When financial institutions require enterprises to connect with the supply chain platform, enterprises conduct supply chain finance cooperation. Due to the large punishment of non-repayment and the existence of block incentives, the income brought by repayment is greater than the income brought by non-repayment, and enterprises will evolve to the repayment decision. When financial institutions do not require enterprises to connect with the supply chain platform, the difference in earnings caused by forged trading information is large under this condition, which exceeds the penalty of non-repayment and the utility generated by repayment, and the enterprise will evolve into non-repayment decision. On the other hand, when an enterprise repayments, the financial institution requires connecting with the supply chain platform to bring more benefits under the current conditions, so it will choose the decision evolution towards the connection of requirements. When an enterprise fails to repay the loan, it will be punished more severely if it fails to connect with the supply chain platform under the current conditions, and financial institutions will choose to evolve to the decision of not requiring the connection [28].

Condition 4: When the enterprise repays, the cost incurred by the financial institutions that do not require the connection of the supply chain platform is relatively small, and the financial institutions will evolve to the decision that does not require the connection; When an enterprise fails to repay the loan, the punishment brought to the enterprise by the connection of supply chain platform is relatively greater, and financial institutions will evolve to the decision requiring the connection [33]. When financial institutions choose to connect the supply chain platform, the punishment for defaulted enterprises is relatively small under the current conditions, and the income brought by non-repayment is greater than the incentive block, so enterprises will evolve to the decision of non-repayment. When financial institutions choose not to connect with the supply chain platform, enterprises will be punished more for not repaying, and the benefits brought by repaying will be greater. Therefore, enterprises will evolve to the decision of repaying. The stable equilibrium decision under the four conditions is calculated [29]. The stability decision of the regulatory risk model under the supply chain application can be obtained from the results in Table 3. The phase diagram is shown below, as shown in Fig. 3.

In Fig. 3, four kinds of evolutionary stability decisions are respectively represented:

(a) No repayment, no docking required;
(b) No repayment and request docking;
(c) Repayment without requiring docking;
(d) Repayment, requiring docking.

When the punishment for the enterprise's default is relatively small, the enterprise's non-repayment income is greater than the income and block incentive brought by the repayment, and the decision of non-repayment will evolve. When the cost of connecting the supply chain platform is relatively high, the financial institution will evolve to the decision that does not require the connection, resulting in the evolutionary stability strategy shown in Fig. 3(a), that is, the enterprise chooses not to repay in pursuit of the benefits of default, while the financial institution chooses not to connect the supply chain platform considering the cost and punishment strength. When docking cost reduction, in order to limit the default behavior of the enterprise, financial institutions will evolve to demand docking decisions, and can produce the evolutionary stable strategy in Fig. 3. (b), when the enterprise is the default penalty is bigger, default by the deterrence, the greater the enterprise will evolve to the decision-making of reimbursement, and can produce the evolutionary stable strategy in Fig. 3. (d); When a financial institution chooses to repay the loan, it will evolve to a decision that does not require docking when considering the high cost of docking. The evolutionary stability strategy shown in Fig. 3(c) will be generated [30].

4.4. Analysis of the influence of parameter changes

Under the condition of supply chain application, the initial position of the system determines the specific equilibrium state of pooling. As

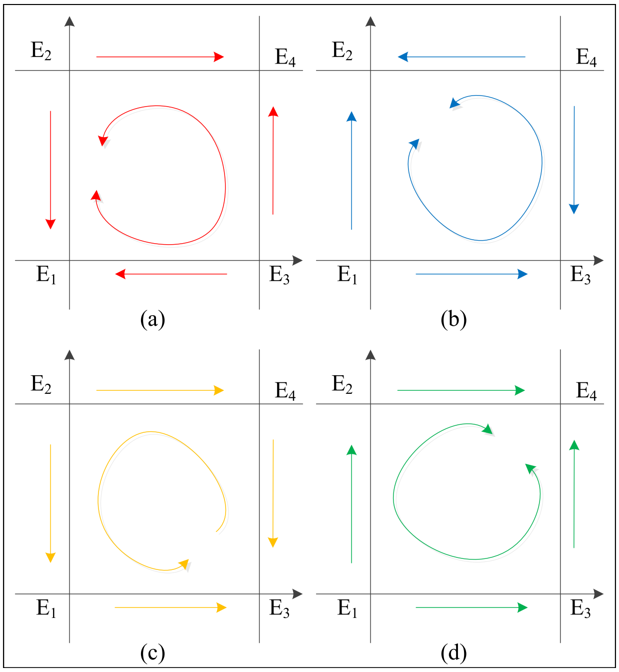

Fig. 3. Phase diagram of supervision model under supply chain application.

can be seen from Fig. 3, under Condition 1, when the attitude of both decision-making parties to supply chain finance cooperation and supervision falls within the quadrilateral $E_2E_4E_3E_5$ region, the cooperation will evolve to $E_4(1,1)$ point, that is, the enterprise chooses to repay the loan, and financial institutions require connecting the supply chain. When the attitude of both decision-making parties to supply chain finance cooperation and supervision falls within the quadrilateral $E_2E_1E_3E_5$ region, the cooperation will evolve to the $E_1(0,0)$ point, that is, enterprises choose not to repay and financial institutions do not require connecting the supply chain [31].

According to Fig. 3, the area of quadrilateral $E_2E_4E_3E_5$ can be calculated as follows:

$$S_3 = SE_2E_4E_3E_5 = \frac{[(1-x_4^*)+(1-y_4^*)]}{2} \tag{23}$$

$$A = \lambda R_2 + (1-\lambda)R_1 - \lambda p_1 - (1-\lambda)P_2 - v \tag{24}$$

$$B = G_1 + p + \lambda R_2 - \lambda R_2 - \lambda R_2 - (1-\lambda)p_2 \tag{25}$$

$$U = \lambda p_1 + (1-\lambda)p_2 - \lambda(C_3 - C_5) - (1-\lambda)(C_4 + C_6) - p + C + H \tag{26}$$

$$V = R_1b_3 - p - \lambda aR_2b_3 - (1-\lambda)aR_1b_3 + \lambda p_1 + (1-\lambda)p_2 - \lambda c_5 - (1-\lambda)c_6 \tag{27}$$

In the case that the remaining conditions remain unchanged, the derivative of each parameter is calculated to judge the influence of parameter changes on S_3, thus obtaining the data anomaly problem of financial institutions.

Model 4

When the default penalty p is larger in the supply chain connection, S_3 is larger, that is, the greater the risk of the trustworthy cooperation of the enterprise, and the greater the risk of the supply chain connection required by financial institutions.

It is proved that the derivative of S_2 with respect to b_2 is:

$$\frac{\partial S_3}{\partial p} = \frac{\left(-\frac{U-V}{V^2} + \frac{A}{B^2}\right)}{2} > 0 \tag{28}$$

According to the constraint conditions of equilibrium point (x_4^*, y_4^*) the value of the above equation is always greater than 0. Therefore, it indicates that when the default penalty p of an enterprise is larger in the connection of supply chain, the greater the risk required by the financial institution is, and the greater the risk of the enterprise's repayment.

Model 5

The larger the R_2 of the forged account, the smaller S_3 is. In other words, the less the risk of the honest cooperation of the enterprise is, the less the risk of the financial institution's request to connect with the supply chain.

To prove that the derivative of S_3 with respect to R_2 is:

$$\frac{\partial S_3}{\partial p_2} = \frac{\left(\frac{-\lambda ab_3}{V^2} + \frac{\lambda(B-A)}{B^2}\right)}{2} < 0 \tag{29}$$

According to the constraint conditions of equilibrium point (x_4^*, y_4^*), the value of the above formula is always less than 0. Therefore, it indicates that when the enterprise forges more R_2, the risk required by financial institutions will be smaller and the risk of repayment will be greater. In this case, enterprises pursue more additional benefits in their decision-making, but the corresponding decisions of financial institutions are not conducive to the development of the supply chain financial market. Even if the audit intensity is increased, there is still a risk of default.

Model 6

When the audit cost c_3, c_4, exposure cost c_5 and c_6 of financial institutions are bigger, S_3 is bigger, that is, the greater the risk of enterprise's trustworthy cooperation and the greater the risk of financial institutions' requirements to connect with the supply chain. It is proved that the derivative of S_3 with respect to c_3 can be obtained in the case of certain other parameters:

$$\frac{\partial S_3}{\partial C_3} = \frac{\left(-\frac{\lambda}{V}\right)}{2} < 0 \tag{30}$$

According to the constraint conditions of equilibrium (x_4^*, y_4^*) type on value less than zero, similarly, the rest of the audit cost and cost of exposure the result is the same, so that when the nuclear financial institutions audit exposure cost of c_3, c_4 and c_5, c_6, the greater the demand docking, the greater the risk of financial institutions to save tedious extra cost, the greater the risk of enterprise repayment.

5. Simulation experiment analysis

In order to fully verify the effectiveness of the proposed method of anomaly data mining in financial supply chain based on the Internet of Things, experimental verification was carried out. In the experimental environment, the enterprise financial supply chain model is proposed based on the Internet of Things. With the precision of serial index, abnormal data identification and abnormal data mining time as experimental comparison indexes, the deep convolution algorithm in this paper is compared with the mining methods of fuzzy neural network and improved clustering algorithm.

The experiment uses three input data with three language variables each, and adopts a mixed parameter training method. After the learning is completed, the obtained corresponding training data has a fuzzy inference system matrix with the smallest root mean square error.

Through adaptive fuzzy neural network for adaptive learning, an inference system is established, and the output result will be a function of linguistic variables, so that the risk value can be predicted. Moreover, the sample will evaluate the subject attributes, object attributes, and environmental attributes in the access control process, which will be quantified through the fuzzy evaluation method to facilitate training and testing, and the results can be fuzzified to establish input language variables. In addition, in order to make the result closer to the displayed value, this sample will select 1000 groups as the training value and 500 groups as the test group. The combination of fuzzy inference based on Takagi–Sugeno and self-adaptation is adapted in the paper.

Table 4
The influence of the maximum number of iterations and the number of experimental samples on the hybrid algorithm.

Maximum number of iterations\experimental samples	15	30	45	60	75
20	6.21%	5.32%	4.48%	4.11%	3.91%
40	6.64%	6.15%	5.34%	4.82%	4.03%
60	4.58%	4.12%	3.52%	2.63%	2.03%
80	4.06%	3.64%	3.17%	2.75%	1.84%
100	3.16%	2.58%	1.67%	1.28%	1.09%

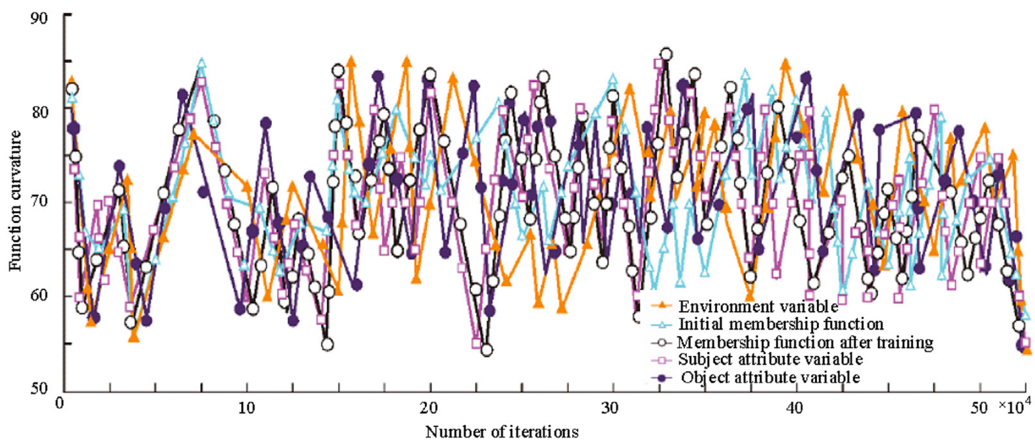

Fig. 4. Membership function curve.

5.1. Risk assessment of adaptive fuzzy neural network

The experimental results have gone through multiple risk assessment tests based on the adaptive fuzzy neural network. After comparing the experimental process and the results, the relevant parameters of the network are set as follows. 1. The Gaussian membership function is selected, and the number of fuzzy language variables is 5. The number of training times is 100, and the expected error is 0.001. 2. A hybrid algorithm combining the error back propagation training algorithm and the least square method is used to train the adaptive fuzzy neural network. When the maximum number of training times is 100, it will converge to an error of 0.001 948 36. The test results of the hybrid algorithm and the number of experimental samples are shown in Table 4.

The membership function curve obtained through learning and training is shown in Fig. 4.

The membership function before training refers to a function of the value of the language variable in the initial state. After learning the existing knowledge, the tendency of the language variables of the samples in the sample set is obtained, namely the degree of membership of the input language variable values. In addition, the greater the degree of membership, the closer to.

The input point it will be, and the more inclined to the language variable represented by the input point it will be.

In Fig. 5, the membership function of each method before training is a function of the value of the language variable in the initial state. After learning the existing knowledge, the tendency of the language variables of the samples in the sample set is obtained, that is, the membership degree of the input language variable value. The greater the membership degree, the closer it is to the input point, and the more inclined it is to the language variable represented by the input point. For the adaptive fuzzy neural network model, the number of language variables in the input layer of the antecedent network is 3, that is, there are 3 risk related elements in the structural model, and the number of outputs of the consequent network is 1, which is the risk value of the result of risk assessment. Through the experimental test, 56 fuzzy rules are output in the middle. The fuzzy rules are obtained by matching the rule fitness calculated by the antecedent network of the adaptive fuzzy neural network with the rules generated by the consequent network.

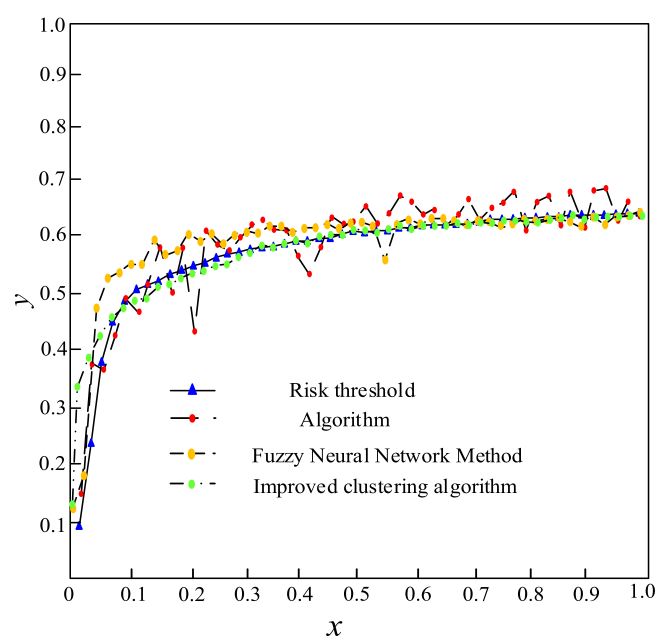

Fig. 5. Membership function curve.

5.2. Comparison of the constraint accuracy of evolution conditions

The precision of evolution constraint has a serious influence on the judgment result of abnormal data, so the precision of evolution constraint is taken as the experimental comparison index. The comparison results of constraint accuracy under evolution conditions are shown in Fig. 5.

In Fig. 5, the risk value is obtained through measurement, and the precision of evolution condition constraint in this paper is basically consistent with the actual value, indicating that the method in this paper can accurately complete the evolution condition constraint and lay a foundation for the accurate mining of abnormal data. However,

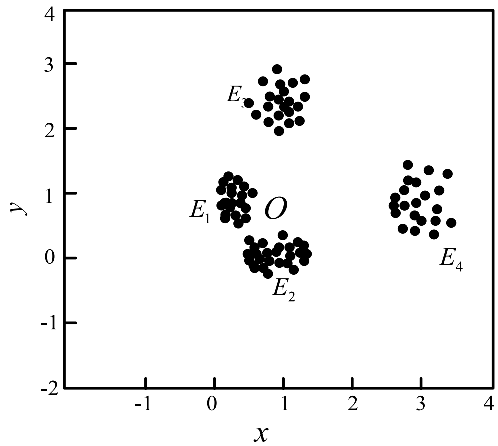

Fig. 6. Dividing abnormal data of deep convolution algorithm.

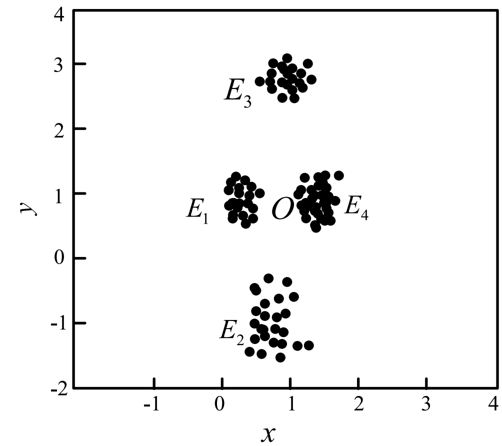

Fig. 8. Fuzzy neural network abnormal data division.

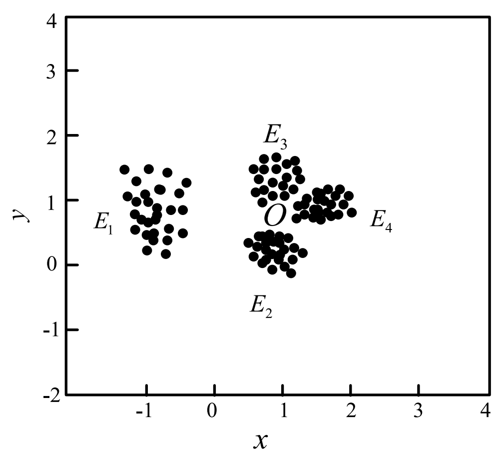

Fig. 7. Dividing abnormal data of deep convolution algorithm.

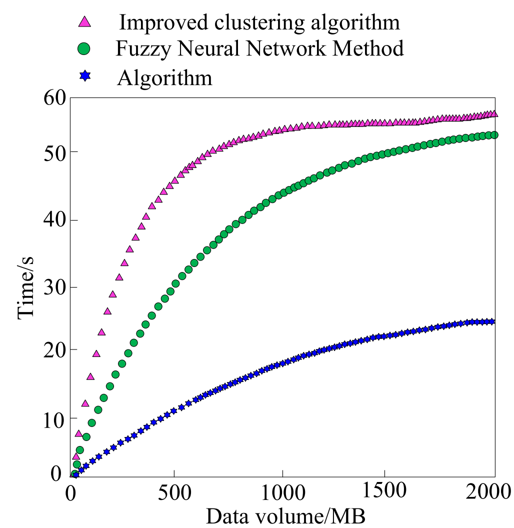

Fig. 9. Dividing abnormal data of improved clustering algorithm.

there is a large deviation between the results of the two comparison methods and the actual values.

5.3. Abnormal data identification

The abnormal data are divided and compared in the two-dimensional data set. E_1, E_2, E_3, E_4 represent the distance field of the data object O, and the farther the distance between E_1, E_2, E_3, E_4 and O in the field indicated that the field contained abnormal data. E_3 and E_4 are set before the experiment to contain abnormal data, while E_1 and E_2 do not contain abnormal data. The abnormal data partition results of the three methods are shown in Figs. 7–9 (see Fig. 6).

According to the setting, fields E_1 and E_2 should be close to the data object O, while fields E_4 and E_3 should be far away from the data object O.

It can be seen from the comparison results that the abnormal data identification results of the proposed method are consistent with the set results, while the two comparison methods both have large errors. The proposed method is to measure the risk of possible abnormal data points in a data set by estimating the child nodes of financial data objects, that is, to measure the degree of isolation of the financial data relative to the surrounding fields. Therefore, the proposed method can accurately identify abnormal data.

5.4. Mining time comparison

In order to prove the practicability of the method in this paper, a data set is randomly selected, which contains 4510 kinds of data objects. 1000 kinds of data objects are selected as the total data of 2 GB in the original data set. The proposed method, the method based on fuzzy neural network and the mining method based on improved clustering algorithm are used to process the data, and the results are shown in Fig. 9.

Through Fig. 10 to see, in the case of increasing quantity of the data, the proposed method of mining time two was always lower than the contrast method, the data volume reached 2000 MB, the proposed method of mining time compared with two kinds of methods of the gap is huge, the proposed method for mining of 24 s, and two methods of mining time reach 57 s and 52 s respectively. Therefore, it is proved that the proposed method has high mining efficiency.

5.5. Numerical example analysis of anomalies

In order to more intuitively describe the evolution of the decision-making parties in the process of supply chain financial supervision, this paper adopts the analysis of abnormal numerical examples and sets the parameter values in combination with the assumption of risk model to verify the conclusions. The model parameter values are shown in Table 5.

Under the condition of constant parameters, the initial values of x and y are fixed respectively. According to the above conditions, the supply chain financial risk model under the application of the

Table 5
Monitor model parameter Settings.

Parameter	Value	Parameter	Value
R	0.7	k	0.7
W	11	G_1	50
R_1	1001	R_2	2999
p	801	p_1	960
b_3	0.07	p_2	800
C_3	11	C_4	1
C_5	1	C_6	11
λ	0.001	v	101
C	1	H	1

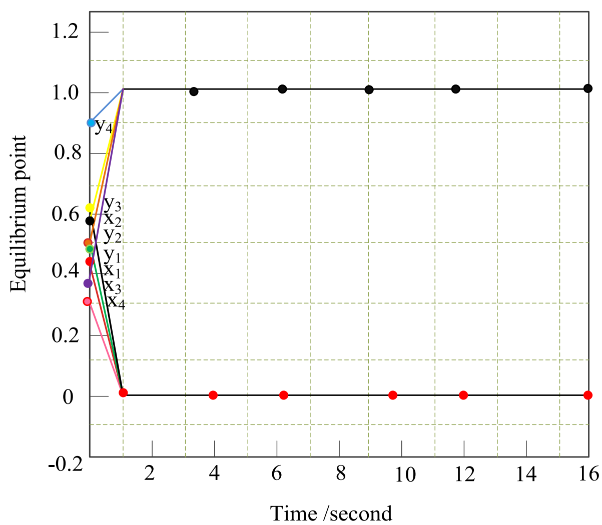

Fig. 10. Comparison of excavation time.

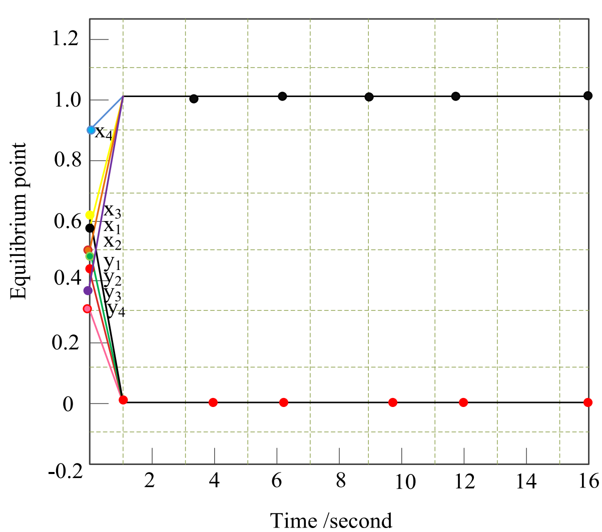

Fig. 11. Dividing abnormal data of improved clustering algorithm.

constructed supply chain is numerically calculated. Fig. 10 shows the fixed y value and Fig. 11 shows the fixed x value.

Figs. 10 and 11 verifies the correlation analysis of evolutionary stability decision in this paper, and The final equilibrium decision of the two parties in the model after joining the supply chain is (repayment, requirement docking) or (no repayment, requirement docking), and its evolution is associated with the initial value of x and y direction. It can be found from the image that when the initial value is low, the two parties are likely to evolve into (no repayment, no docking required). When the initial value exceeds a certain value, the two parties will evolve into (repayment, no docking required). However, the critical value is higher, and there are certain barriers for the supply chain combining with the new technology of supply chain finance to join the market.

6. Conclusion

Traditional supply chain finance cooperation needs to be clear about the punishment and to keep good operation in the long run. For the traditional cooperative game model of supply chain finance, the decision-making parties are core enterprises and SMEs. Under the assumption of the traditional model, the evolution results are rarely "double good faith". When medium, small and micro enterprises default and fail to repay, the core enterprises have the tendency of late repayment. The higher the penalty imposed by a financial institution or the efficiency of a well-functioning supply chain, the higher the probability of the two parties cooperating in good faith.

With return matrix by calculation, regulatory risk model in this paper gets the evolution model of risk balance situation, and analyzes the different parameter values range when the risk model of equilibrium decision combination, and further analyzes the influence of parameter change on the evolution of probability, finally, a numerical example is given to show the decision evolution of both sides.

The core enterprises and small, medium-sized and micro enterprises studied in this paper do not reflect the degree of information symmetry and information exchange efficiency between them. In fact, enterprises often experience multi-layer links. Therefore, in the future, relevant parameters such as information level, enterprise scale and information asymmetry can be further added for game model construction and decision-making analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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