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Research Article

Hydrological Layered Dialysis Research on Supply Chain Financial Risk Prediction under Big Data Scenario

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In recent years, internet development provides new channels and opportunities for small- and middle-sized enterprises' (SMEs) financing. Supply chain finance is a hot topic in theoretical and practical circles. Financial institutions transform materialized capital flows into online data under big data scenario, which provides networked, precise, and computerized financial services for SMEs in the supply chain. By drawing on the risk management theory in economics and the distributed hydrological model in hydrology, this paper presents a supply chain financial risk prediction method under big data. First, we build a "hydrological database" used for the risk analysis of supply chain financing under big data. Second, we construct the risk identification models of "water circle model," "surface runoff model," and "underground runoff model" and carry on the risk prediction from the overall level (water circle). Finally, we launch the supply chain financial risk analysis from breadth level (surface runoff) and depth level (underground runoff); moreover, we integrate the analysis results and make financial decisions. The results can enrich the research on risk management of supply chain finance and provide feasible and effective risk prediction methods and suggestions for financial institutions.

1. Introduction

Internet development provides new channels and opportunities for SME financing. Supply chain finance (SCF) is a recent stream of research aimed at optimizing financial flows through solutions implemented by financial institutions [1]. As a new theory, supply chain finance is still in the exploratory stage in practice, especially in risk management and control. The research on the theory of supply chain financial risk prediction is far behind the actual application requirements [2]. The relevant references are mainly concentrated on the following two aspects. The first category focuses on the conceptual and theoretical aspect of supply chain finance. Berger [3] first put forward some new ideas and new frameworks for the financing of SMEs. Kaplan [4] proposed the concept of "electronic center" and established a supply chain aggregation model. Buyers and sellers can provide financial services in the "electronic center" field. Corning [5] proposed that B2B e-commerce transactions created conditions for real-time financing, and B2B transaction participants should form alliances with financial service organizations to develop credit, financing, and dispute processing services. Basu [6, 7] conducted a research on the prepayment financing model and pointed out that the prepayment of financing orders could effectively solve the lag problems of logistics, and established an online data analysis platform. He believed that online supply chain finance played an important role in shortening the repayment period. Swift [8] believed that online supply chain finance integrated all parties in the supply chain, improved information exchange data and business operation efficiency, and reduced financing costs. Templar [9] pointed out that SCF is at the evolutionary frontier of financial services that are closely related to the supply chain cycle. Kouvelis [10] studied the impact of credit ratings on operational and financial decisions of a supply chain with a supplier and a retailer interacting via an early payment discount contract. Hofmann [11, 12] proposed an approach that allows all parties involved in supply chain finance to

improve the working capital and creates a win-win situation; and he believed that blockchain technology played an important role in accelerating capital flow in online supply chain finance projects. The second category focuses on the risk prediction of supply chain finance. Tsai [13] proposed a cash flow risk model using the standard deviation between cash inflows, outflows, and net cash flows at different time periods to perform risk control to predict the company's risk. Ralf [14] believed that the core companies in the supply chain should make choices in the relationship between supplier capital occupation and supplier relationship maintenance in order to prevent risk transfer. David [15] comparatively analyzed the risks and risk management methods of supply chain financial management before and after shipment and established the infrastructure of supply chain financial management. Bandaly [16] pointed out that the risk occurrence in any node of supply chain finance was very likely to lead to the risk of the entire supply chain, resulting in the collapse of the entire supply chain. Trott [17] specifically proposed the role of supply chain financing in promoting the development of SMEs, pointing out that the risk sources mainly came from finance and operations. Peter Finch [18] pointed out that the nonimprovement of information systems would increase the risk exposure level of banks, and he specifically emphasized that it was necessary to strengthen the ability of small and micro enterprises to continue their operations and pay close attention to the capacity of supply chain financial information systems. Yu [19] used LDSPPC model to reveal the linear relationship of financial risk level of online supply chain. Yan [20] constructed a Stackelberg game in supply chain finance system and found that incorporating bank credit with a credit guarantee can effectively balance the retailer's financing risk between the bank and the manufacturer through interest rate charging and wholesale pricing. Chen [21] builds a two-stage supply chain financial decision model on the order quantity and wholesale price. Babich [22] pointed out that risk management is a promising direction for supply chain finance.

Different from the above research work, this paper addresses the key issues in risk management in the process of supply chain financing under big data. We adopt distributed hydrological model to build the "hydrological database" and, respectively, construct surface runoff model and underground runoff model to conduct the risk prediction from the breadth and depth dimensions. Finally, we integrate and aggregate the analysis results to determine the risk level of the financing enterprise, which help the financial institutions to make financing decisions.

2. Model Description

2.1. General Description of the Hydrologic Model

2.1.1. Water Cycle Process. The water cycle includes several major links, such as precipitation, runoff, canopy retention, infiltration, and evaporation. In many of these links, there will be conversions of matter and energy and the transformation of water volume. At the same time, the water cycle will also be influenced by atmospheric precipitation, weather and climate changes, and other factors such as landforms, topography, and human activities. Therefore, the water cycle is a very complicated process, which is shown in Figure 1.

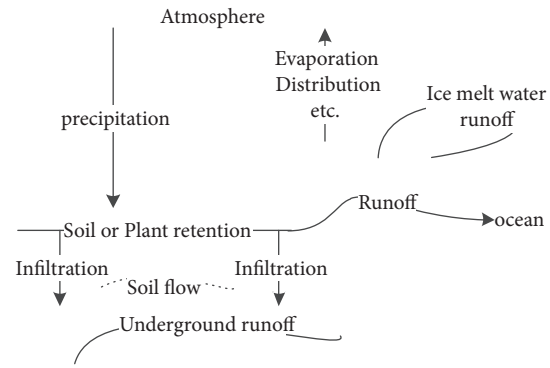

Figure 1: Schematic diagram of water circle cycle model.

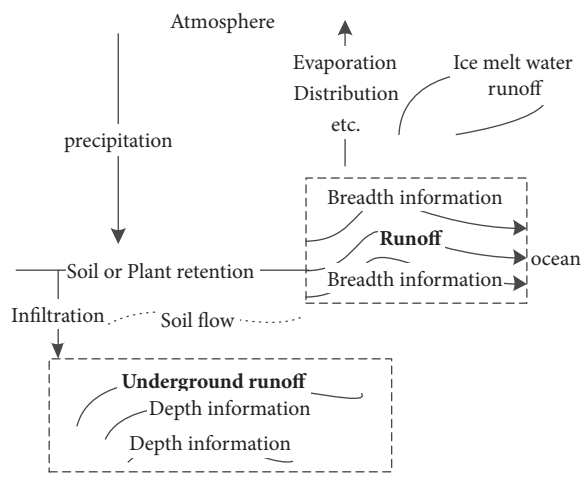

Figure 2: Schematic diagram of surface runoff model and underground runoff model.

All the solid, liquid, and gaseous tristate waters on Earth constitute the water circle of the earth. While the conditions are stable, the vapor in the atmosphere condenses and falls to the surface in the form of precipitation and under the action of the earth's gravity. Part of the precipitations return to the atmosphere through evaporation and distribution, and some precipitations form the surface runoff and finally flow into the ocean; and some precipitations flow into the soil to form a midstream stream; and some precipitations penetrate deep into the ground to form underground runoff [23]; some precipitation is formed at high latitudes and forms glacial snow, which melts and forms ice-melted-water runoff. The water bodies in the hydrosphere follow the cycle of gravity and solar radiation, and this process is called water circle cycle. The submodels included in the water cycle are as follows: "evapotranspiration" model; "surface runoff" model; "soil flow" model; "subterranean runoff" model; "ice-melting water runoff" model. Each model has its own characteristics, which is shown in Figure 2.

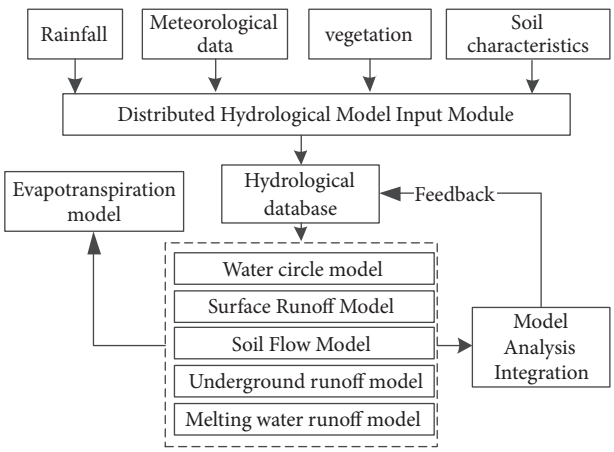

Figure 3: Risk prediction flow chart based on the distributed hydrology model.

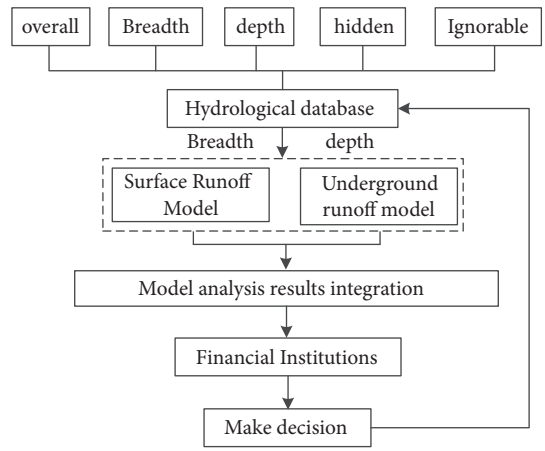

Figure 4: Financial risk prediction process based on hydrological layered dialysis method.

2.1.2. Distributed Hydrological Model. Hydrology experts have invented and developed various methods and theories of flood forecasting from the unexplained rules of flood outbreaks that had caused mankind many great disasters. Hydrological model is one of them [23]. By using physical models and mathematical parameters to describe the actual hydrological system, it simulates and predicts the dynamic hydrological variables in the hydrological system under certain conditions. Among hydrological models, the distributed hydrological model is most widely used, and the mathematical model of the hydrological process of a certain watershed is simulated by the method of water cycle dynamics. The distributed hydrological model is a simplified representation of a complex hydrological system that is generally summarized and abstracted by academic community.

Distributed hydrological models have good early warning effects on floods. The working process is as follows: the river hydrological data (including rainfall, meteorological data, vegetation, and soil characteristics) are input into the distributed hydrological model, and the hydrological database summarizes and stratifies the data. The layered data are input into the water circle model, surface runoff model, soil flow model, underground runoff model, and melting water runoff model for analysis and integration to predict the flood. The final result is fed back to the hydrological database, as shown in Figure 3.

2.2. Supply Chain Financing Risk Prediction Based on Hydrologic Model. In this section, we apply the distributed hydrology model to the supply chain finance field and propose a supply chain financial risk prediction model based on hydrological layered dialysis method under big data scenario. We focus mainly on two models of surface runoff and underground runoff for risk prediction. The flow chart is shown in Figure 4.

The process of hydrological layered dialysis model for forecasting supply chain financial risk based on big data scenario is as follows: we firstly establish a "hydrological database" through collecting data on the trading volume of financing companies, bank cash, inflow and outflow data, and the value of changes in the credit index of small- and medium-sized enterprises. The "hydrological database" covers data for multiple dimensions of financing companies, including overall, breadth, depth, concealment, negligible, and external stimulus data. Among these, the overall data refers to the basic data of the financing enterprise itself for the current year; the breadth data refers to the data of other similar companies in comparison with financing companies; the in-depth data refers to the historical data that the financing companies themselves need to dig in depth; the covert data refers to the financing company's own opaque, undisclosed data, and the negligible data refers to data that has minimal impact on the company's own risk; the external stimulus data refers to data that cannot be controlled by the enterprise itself and is generated through external stimulation. In this paper, we mainly focus on the breadth and depth data for risk prediction. The collected breadth and depth information are used to determine the risk status of financing companies through "surface runoff" and "underground runoff" model analysis. Finally, through the integration of model analysis results, the bank makes final financing decisions.

2.3. Hydrological Layered Dialysis Model Description for Supply Chain Financing Risk Prediction

2.3.1. "Water Circle" Model. The risk evaluation indicator system in "water circle" model is established. In hydrology, people often set accommodation values for rivers, and there is a higher probability of flood peaks while this accommodation value is approached.

In the field of supply chain finance, banks also have such accommodation value while predicting financing risks. While the predicting risk value is close to the accommodation value, banks will probably face default risk. In this paper, we take risk theory and literature review as reference and construct a supply chain financing risk indicator system, which is shown in Table 1.

Table 1: Supply chain financing risk indicator system based on "water circle" model.

First-level indicators	Second-level indicators	Third-level indicators
Macro level	Business scenario risk indicators	Macro System Risk
		Industry System Risk
Meso level	Supply Chain Risk Indicators	Supply chain stability
		The degree of supervision of logistics enterprises
	Core corporate risk indicators	Enterprise strength
		Profitability
		Credit ability
		Short-term solvency
Micro level	Financing Enterprise Risk Indicators	Corporate quality
		Management capacity
		Currency funds (profitability)
		Solvency
		Development ability
	Collateral risk indicators	Inventory
		accounts receivable
		Prepayments

2.3.2. "Surface Runoff" Model

(1) The Risk Evaluation Indicator System in "Surface Runoff" Model Is Established. When extracting breadth information from hydrological database, considering the criterion of "easier to obtain and more representative compared with similar related financing enterprises," we select six types of indicators with greater weight for "surface runoff" model establishment from the "water circle" indicator system. The indicator system contains the scale of financing companies, the cooperation closeness with upstream and downstream companies, the return rate of tangible assets, the asset-liability ratio, the quality of revenue from operating activities, and the ratio of cash flow liabilities. At the same time, the repayment risk levels of similar enterprises are extracted from the hydrological database. These seven type indicators are used as the basis for establishing the "surface runoff" model.

Based on this, we select a sample of financing data and adopt the decision tree analysis method where seven types of indicators are used as nodes. Firstly we divide the samples to form a decision tree and then transform it into a rule set and use the pessimistic estimation to determine whether a pruning is needed and a classification rule set is constructed; lastly we obtain a set of "surface runoff" credit risk classification rules, as shown in Table 2.

(2) "Surface Runoff" Risk Prediction Model Based on Naive Bayesian. Naive Bayes is a prediction method for risk classification. It is characterized by pruning and classifying various reference indicators and objectively predicts the risk of a certain object through model calculation. Therefore, it is widely used in the supply chain risk management field. This section adopts Naive Bayes method to construct a "surface runoff" risk prediction model.

The model establishment process is as follows: we assume that X is a data sample and C is the class label. The task of naive Bayes classification is to assign the unknown sample X to C_i with the highest posterior probability, where $P(C_i \mid X) > P(C_j \mid X)$, $1 \leq j \leq m$, $i \neq j$. At this point, the maximum $P(C_i \mid X)$ corresponding to the highest posterior probability C_i is called the maximum posteriori assumption. According to Bayes' theorem, we obtain that

$$P(C_i \mid X) = \frac{P(X \mid C_i) P(C_i)}{P(X)}. \quad (1)$$

Among these, $P(C_i)$ represents the prior probability and $P(X \mid C_j)$ represents the conditional probability. If the prior probability $P(C_i)$ is unknown, then it is assumed that the classes are of equal probability; that is, $P(C_1) = P(C_2) = P(C_3) = \ldots = P(C_m)$. If $P(C_j)$ is known, then maximize $P(X \mid C_j)P(C_j)$, the prior probability is obtained with $P(C_j) = s_j/s$, where s_j is a training sample of C_j, and s is the total number of training samples. If the complex dataset has multiple attributes, then $P(X \mid C_i)$ is difficult to be solved. At this time, we can make simple assumptions of independent conditions.

Based on the above steps, the risk status of the financing company can be calculated by adopting "surface runoff" model under "breadth information" condition.

2.3.3. "Underground Runoff" Model

(1) The Risk Evaluation Index System in the "Underground Runoff" Model Is Established. According to a 2008 Aberdeen Group Research Report on "Supply Chain Financial Market State," four historical indicators that best reflect the financial performance of the supply chain are cited in the

Table 2: Credit risk classification rule set for corporate loan.

Attribute name	Ranges
Financing enterprise size	Large, medium and small
Cooperation with upstream and downstream companies	High, Medium and Low
Return on tangible assets	>40, ≤40
Assets and liabilities	>15,8-15,<8
Business activity revenue quality	>90, ≤90
Cash flow to debt ratio	>0.8, ≤0.8
Repayment risk (risk rate)	High, Medium and Low

establishment of the "surface runoff" model indicator system. We adopt monetary fund, accounts receivable, prepayment amount, and inventory amount as key indicators for analyzing the depth information of "underground runoff" model.

(2) "Underground Runoff" Risk Prediction Model Based on Cusp Mutation. The cusp mutation is a method of predicting the risk mutation. The characteristic is to discuss the risk through mutation. We use cusp mutation method to construct "underground runoff" risk prediction model.

The model establishment process is as follows: the cusp abrupt balance surface has a bifurcation set B. If the control variables in the surface cause the changing of the state variable while passing through the bifurcation set B and generate a sudden change, then the system will face unstable situation; if the control variables do not pass through the bifurcated set B, then the state variable is stable and the system is stable.

The cusp mutation function equation is $V(x) = x^4 + mx^2 + nx + c$. In the formula, m, n are control variables and x is a state variable. Assume that $V'(x) = 0$, and then we derive the equilibrium surface equation: $4x^3 + 2mx + n = 0$. Furthermore, we assume that $V''(x) = 0$ and find the set of function singularities $12x^2 + 2m = 0$. After pairing the balanced surface with the singularity set, we obtain the bifurcation set, $8m^3 + 27n^2 = 0$, and the forked set is a set of points in a balanced surface that allows all x to jump. The real roots number of the equilibrium surface equation needs to be determined by the sign of the discrimination $\Delta = 8m^3 + 27n^2$. The results can be divided into four situations: $\Delta > 0$ stands for the fact that the system is stable; $\Delta = 0$ represents that the critical value of system is stable; while $\Delta < 0$ and the error between the mutation and the normal value is within 1/3, it means the system is relatively stable, and while $\Delta < 0$ and the error between the mutation and the normal value is more than 1/3, it means the system is instable. Based on the above analysis, it is possible to calculate the risk status of the financing company by "underground runoff" model under "depth information."

3. Empirical Analysis

Shenli company ("S" for short) is a professional company specializing in the production of lifting equipment and supporting products. At present, in order to meet the customers' demand, S puts forward the plans for expanding the production scale and introducing high-quality products. However, it is difficult to quickly realize large-scale and specialized production based on its own funds. For this large funding gap, S applies 9 million RMB from M financial institution to ease financial pressure.

By investigation, M financial institution discovers that S relies on a core company in the supply chain. The cooperations between the two parties have been lasting for a long time and the business exchanges are stable. However, there are some certain risks in this loan. Therefore, M financial institution should analyze the financing risk of S. We extract the indicator data of the S's breadth (surface runoff) and depth risk level (underground runoff) from the constructed "Hydrology Database" based on big data. Suppose that M financial institution has finished the "water circle" model selection, and then the risks of "surface runoff" and "underground runoff" models are needed to be constructed.

3.1. Application for "Surface Runoff" Risk Evaluation Model. The breadth level (surface runoff) data of S was analyzed by Naive Bayesian method. The M financial institution extracts the "surface runoff" indicators data of 15 companies of the same type from the "hydrological database," which is shown in Table 3.

The surface runoff data of S is X = (Financing enterprise size = "6401", Business activity revenue quality = "87", Cooperation with upstream and downstream companies = "Medium", Return on tangible assets = "41", Asset investment rate = "18", Cash flow to debt ratio = "1.1").

(1) Prior probability: P(Repayment risk "Low") = 0.6, P(Repayment risk "High") = 0.4;

(2) Conditional probability:

P (Financing enterprise size = "6401"/Repayment risk "Low") = 0.33;

P (Business activity revenue quality = "87"/Repayment risk "Low") = 0.22;

P(Cooperation with upstream and downstream companies = "Medium"/Repayment risk "Low") = 0.44;

P (Return on tangible assets = "41"/Repayment risk "Low") = 0.67;

P (Asset investment rate = "18"/Repayment risk "Low") = 0.44;

P (Cash flow to debt ratio = "1.1"/Repayment risk "Low") = 0.78;

Then: P (X/Repayment risk "Low") = 0.00734;

Table 3: Surface runoff indicators data for financing enterprises extracted from hydrological model database.

number	Financing enterprise size	Business activity revenue quality	Cooperation with upstream and downstream companies	Return on tangible assets	Asset investment rate	Cash flow to debt ratio	Repayment risk
1	≤4000	>85	Medium	>45	>15	≤1.3	Low
2	>40000	>85	High	≤45	>15	≤1.3	Low
3	>40000	>85	High	≤45	8-15	≤1.3	Low
4	4000-40000	≤85	Low	>45	8-15	≤1.3	High
5	4000-40000	>85	High	≤45	>15	≤1.3	Low
6	4000-40000	≤85	Medium	>45	8-15	>1.3	High
7	4000-40000	>85	Medium	>45	<15	<1.3	Low
8	4000-40000	>85	Low	≤45	<8	>1.3	High
9	4000-40000	≤85	Medium	≤45	<8	>1.3	High
10	4000-40000	≤85	Medium	≤45	<8	≤1.3	Low
11	≤4000	>85	Medium	≤45	8-15	>1.3	Low
12	≤4000	>85	Low	>45	<8	≤1.3	High
13	>40000	>85	High	>45	>15	>1.3	Low
14	≤4000	≤85	Low	>45	>15	>1.3	High
15	≤4000	>85	Low	>45	8-15	≤1.3	Low

Table 4: Underground runoff indicators data for financing enterprises extracted from hydrological model database.

Year	2010	2011	2012	2013	2014	2015	2016
Accounts receivable	170	1228	1841	3331	1784	1379	1499
Prepayments	661	1768	1361	1729	2123	2089	2361
currency funds	128	9	320	339	253	418	459
Inventory	1701	1231	1901	2339	2641	2491	2129

P (Financing enterprise size = "6401"/Repayment risk "High") = 0.67;

P (Business activity revenue quality = "87"/Repayment risk "High") = 0.67;

P(Cooperation with upstream and downstream companies = "Medium"/Repayment risk "High") = 0.33;

P (Return on tangible assets = "41"/Repayment risk "High") = 0.33;

P (Asset investment rate = "18"/Repayment risk "High") = 0.33;

P (Cash flow to debt ratio = "1.1"/Repayment risk "High") = 0.33;

Then: P (X/Repayment risk "High") = 0.00532;

(3) The result is calculated:

P (X/Repayment risk "Low")P(Repayment risk "Low") = 0.004404;

P (X/Repayment risk "High")P(Repayment risk "High") = 0.002936;

From the above analysis, we find that the probability of low repayment risk of the financing enterprise is greater than the probability of high repayment risk. Therefore, through the analysis of (breadth level) surface runoff data through the hydrological layered dialysis model, the risk probability of the S is predicted to be "low."

3.2. Application for "Underground Runoff" Risk Evaluation Model. The depth level (underground runoff) index data extracted by the "Hydrology Database" is shown in Table 4. We take the "year" as the independent variable X and take the four vertical index datasets as Y, using the least squares method in Matlab software to fit the quartic function of the cusp mutation.

Firstly, we calculate the fourth-order polynomial by fitting the accounts receivable, which is shown in formula (2):

$$Y_{\text{Accounts receivable}} = 39.28x^4 - 594.12x^3 + 2794.21x^2 - 3979.75x + 1944 \tag{2}$$

This is the fitting curve and error curve for 2010-2016, as shown in Figure 5. The blue line is the actual value, the red line is the fitting value, and the yellow line is the error curve value.

Secondly, we analyze the accounts receivable mutation. The functional equations of the cusp catastrophe model are derived from the polynomials through elementary changes. Set the polynomial as formula (3):

$$y(m) = a_1m^4 + a_2m^3 + a_3m^2 + a_4m + a_0 \tag{3}$$

Since there are no cubic terms in the cusp catastrophe model, we can make $m = x - n$, $n = a_2/4a_1$, and the above formula can be changed to formula (4):

$$F(x) = b_1x^4 + b_2x^2 + b_4x + b_0 \tag{4}$$

among which, we get formula (5):

$$\begin{bmatrix} b_0 \\ b_4 \\ b_2 \\ b_1 \end{bmatrix} = \begin{bmatrix} n^4 & -n^3 & n^2 & -n & 1 \\ -4n^3 & 3n^2 & -2n & 1 & 0 \\ 6n^2 & -3n & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_0 \end{bmatrix} \tag{5}$$

Then we can make $V(x) = F(x)/b_1$ to perform variable substitution, and then we get the standard function of the cusp catastrophe model as shown in formula (6):

$$V(x) = x^4 + ux^2 + vx + c \tag{6}$$

We can perform an elementary transformation on formula (2) and then get $n = a_2/4a_1 = -3.78$, $b_0 = 2756.20$, $b_4 = 163.50$, $b_2 = -575.63$, $b_1 = 39.28$. Then through variable substitution, we obtain $u = -14.65$, $v = 4.16$, $c = 70.17$.

The cusp mutation function is shown in formula (7):

$$V(x) = x^4 - 14.65x^2 + 4.16x + 70.17 \tag{7}$$

The bifurcation set is calculated as $8u^3 + 27v^2 < 0$.

Using the same cusp catastrophe analysis method, we obtained that the bifurcation sets for the prepayments, currency funds, and inventory are also less than zero by calculating the prepayments.

For S, despite the abrupt changes in accounts receivable, prepayments, currency funds, and inventory, we suppose that the reason is the sharp increase in business volume during the company's own development process and the temporary shortage of working capital. Observing the data carefully, we can see that the absolute values of the error for the four indicators during the recent seven years are within one-third of the average value of the actual value, which indicates that the system mutation is benign despite the deterioration of the stability of the mutant system. Therefore, M financial institution can properly provide loan service for S. For the actual amount of financing provided by M financial institution, refer to Table 5.

Table 5: The actual financing amount provided by M financial institution.

error	0	>0 and <1/3
Financing amount	F	2F/3

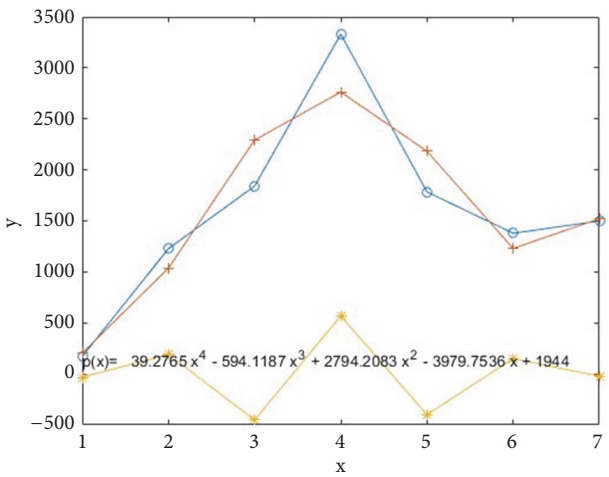

Figure 5: Fitting curve and error curve of accounts receivable.

3.3. Integration Analysis for the Model Results. The integration analysis process is as follows: firstly, the trader S will establish a "water circle" risk assessment indicator system and enter the "hydrological database." Then, relevant horizontal (breadth level) data will be extracted from the "hydrological database" and be accepted by the "final runoff" classification prediction model of the M financial institution. If the M financial institution assesses that its risk is "low," then it proceeds to the next step. If the risk is "high," the M financial institution rejects the loan; finally, it extracts relevant vertical (depth) data from the "hydrological database" and accepts the "underground runoff" pointer mutation model screening. M financial institutions list three options for traders S: if condition 1 is satisfied, which means the fork set is greater than 0, then M financial institutions will provide traders with 9 million RMB of financing; if condition 2 is satisfied, which means the fork set is less than 0, but the error is within 1/3 of the average value of the actual value, then the financial institution will provide a financing amount of 6 million RMB. If condition 3 is satisfied, which means the fork set is less than 0 and the error is outside 1/3 of the actual value, then the financial institutions will refuse to provide loans.

Through the surface runoff model and the underground runoff model to analyze and forecast the financing risk of enterprise from the breadth and depth levels, the bank ultimately decides whether to finance the enterprise, so as to maximize the return of the bank under the premise of the lowest risk.

4. Conclusions

The purpose of establishing a hydrological model is to predict the possible risk status of a certain river basin in advance. This paper applies the forecasting principle of the hydrological model to the supply chain finance field and predicts the risk status of the financing enterprise in advance based on the hydrological layered dialysis model of the supply chain financial risk forecast under the big data scenario, which reduces the loan risk of financial institutions. Based on the hydrological database made by real time data, a quantitative analysis method is used to construct hydrological layered dialysis model and the financial institutions decide whether or not to lend financing companies through multidimensional and dynamic forecasting and evaluation of corporate financing risk based on supply chain under big data scenario.

We adopt the two dimensions of "surface runoff" and "underground runoff" to determine the financial risk; however, the indicators are not comprehensive. In the future research, the indicator system can be further improved by considering the risks in combination with the other models which can more effectively reduce the financing risk of financial institutions.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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