

Improved Whale Optimization Algorithm for supply chain financial risk assessment of cloud warehouse platform

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ABSTRACT

This study provides an in-depth analysis of a new financial model for cloud warehouses and evaluates the associated credit risk within the context of supply chain financing, focusing on the intelligent transformation in this field. Concurrently, an optimization problem was derived from the evaluation issue, with the whale optimization algorithm (WOA) used to identify a reasonable default point and distance. To simplify the identification of these points, we enhanced the traditional WOA, resulting in an improved version, the IWOA, which demonstrated very good optimization performance. The IWOA's optimization capabilities were applied to determine the optimal ratio of short- and long-term debt coefficients, identifying the default point in the Kealhofer, McQuown, and Vasicek (KMV) credit monitoring model, replacing fixed values and yielding more precise results. Furthermore, this study introduces a novel analytical approach to credit risk measurement, advancing the development of related theories and methods. Accurate analysis of financial stability and risk is crucial in industrial sectors, including engineering and manufacturing. The simulation using specific data revealed that the IWOA-KMV model exhibited better and faster optimization capabilities, with greater discrimination ability compared to the KMV model. Overall, this study examines the risk factors in the cloud warehouse financing model, offers an improved version of the WOA, introduces a modified IWOA-KMV model to create a scientific, practical credit risk assessment framework, and provides guidance for risk control in cloud warehouse financing, a novel financing service.

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1. Introduction

Smart logistics reforms have promoted the development of supply chains. Adapting to the trend of intelligent warehousing has becoming increasingly difficult with advances in science and technology. In recent years, new warehousing services such as *pre-warehouse*, *lightning warehouse*, *unmanned warehouse*, and *satellite warehouse* have continuously emerged [1]. A cloud warehouse is a common storage solution that leverages cloud computing, the Internet, and other information technology and presents a management approach that extends beyond traditional warehousing services and idle storage facilities. The cloud warehouse platform for supply chain finance services utilizes information technologies such as cloud computing and the Internet of Things (IoT) to simultaneously collect and analyze supply chain information and provide financing channels for supply chain enterprises [2]. Through the standardization of warehouse receipt pledge financing, supply chain enterprises can offer credit guarantees to financial institutions, enhancing regulatory support for financial institutions and effectively reducing barriers associated with factual

information. However, the cloud warehouse platform that provides financial services for business enterprises also presents a new challenge in supply chain financing. The liquidity, uncertainty, and market volatility characteristics associated with using receipts as pledges in the supply chain financing of products from a warehouse make it difficult to assess pledge value and control credit risk [3]. Li *et al.* studied an algorithm that combines adaptive nonlinear convergence factor with variable gain compensation mechanism, adaptive weighting and advanced spiral convergence strategy, which improves the global search ability, convergence speed and accuracy of the WOA algorithm [4]. Therefore, considering the new characteristics and needs of the existing market, this study combines the improved whale optimization algorithm (IWOA) and the Kealhofer, McQuown, and Vasicek (KMV) model to carry out financial credit evaluation, which has more comprehensive search capabilities and obvious distinctions, creating a new model that evaluates the financial credit risks involved in cloud warehouse platforms more effectively.

The study focuses on the unique credit risk challenges in supply chain finance faced by small and medium enterprises (SMEs). It elaborates and analyzes existing credit risk assessment theories and strategies considering the risk factors in the supply chain analysis of a cloud warehouse. Based on this, the WOA was modified in three ways to address model calculation issues, and the KMV model was built to provide decision support for the supply chain financial risk assessment system. The usefulness of the proposed model for supply chain financial risk assessment was clearly confirmed through an example.

The remainder of the paper is structured as follows. In Section 2, a literature review is introduced, and in Section 3, the proposed approach is outlined. In Section 4, the IWOA-KMV credit risk assessment model is presented, and in Section 5, a simulation study of this model is presented. Finally, in Section 6, the conclusions are presented.

2. Literature review

2.1 Research status of the cloud warehouse platform

In recent years, the cloud warehouse platform has attracted widespread attention. Dobrescu *et al.* argued the need to combine cloud computing with supply chain networks to make them more intelligent, highlighting the importance of considering scientific and technological advancements in informed decision-making [5]. Song *et al.* proposed building a comprehensive information platform to solve information asymmetry problems in traditional supply chains [6]. In the era of information networking technology, virtual supply chains conduct transactions through information-sharing platforms, which can reduce information barriers and improve supply chain flexibility. Chai designed a conceptual model of an information platform based on blockchain technology by analyzing the factors affecting the construction of a supply chain information platform, emphasizing both the business process and economic model [7]. Noting the widespread implementation of blockchain technology in various territories, Lee highlighted that information system reviews needed to be more comprehensive to clearly assess the relative level of use of this technology [8]. Marza *et al.* established an evaluation framework based on the analytical hierarchy process (AHP) for coordinating the levels of finance and digitalization. Taking the data of five Eastern and Central European countries as an example, it was found that finance and digital water fortresses required government intervention for improved coordination results [9]. Deng introduced the concept of *cloud* technology to drive innovation in supply chain financial services and proposed the *cloud warehouse* model, emphasizing sharing as its core principle. He explored the integrated services and continuous spot trading mechanism enabled by this model, aiming to foster a multi-party win-win scenario. Furthermore, in terms of risk management, Pan *et al.* used the risk-adjusted return on capital (RAROC) method to establish a loan pricing model under the *cloud warehouse* financing mode, which exploited the powerful information collection function of a cloud warehouse and assisted financial institutions in avoiding risks and improving yield [11]. In the development direction of the cloud warehouse platform, Chinese enterprises have given more consideration to the diversity of services, combined with supply chain financial services, to solve the capital problem for small and medium-sized enterprises. Cloud warehouses, a new model of

warehouse management and supply chain financing services, along with the associated management risks and problems, are gradually becoming a popular research direction.

2.2 Research status of supply chain financial risk

In supply chain financing, warehouse receipt pledges help reduce the financial risks of SMEs. Wang *et al.* discussed the core index of warehouse receipt pledge risk control, specifically focusing on the pledge rate [3]. Wang *et al.* elaborated on the dangers of warehouse receipt pledge financing and the accompanying risk-management techniques, particularly those used by fourth-party logistics firms [12]. Zhang *et al.* developed a credit risk index system, a SVM, and a back propagation neural network model to assess the credit of top supply chain companies [2]. Li *et al.* use random forest and logistic regression classifications to evaluate the materiality and credit risk of P2P firms, identifying loan targets with a high probability of default [13]. Malhotra conducted an in-depth analysis of the identification of bad credit applications. Discovering that the neuro-fuzzy system outperformed other methods in identifying bad credit applications, he improved this system to assess the risk level of financial enterprises [14]. To address the capacity combination problem of contract manufacturers, Zheng and Bao proposed a uniform variation artificial fish swimming algorithm (AFSA_UM) with a good convergence performance and strong robustness [15]. Esmaili-Najafabadi *et al.* used the particle swarm optimization (PSO) algorithm to provide the solution to a mixed-integer nonlinear programming (MINLP) model for supplier selection and order allocation in a centralized supply chain that considered risk avoidance and interruption risk decision makers [16]. Liu and Huang introduced the integrated SVM model for risk assessment in supply chain finance [17]. Based on data from small and medium-sized enterprises in China, Du *et al.* compared six commonly used machine learning classification models and found that neural networks, support vector machines, and GBDT models performed better [18]. Warehouse receipt pledge financing is an important method in supply chain financing, and targeted evaluation models have been developed by many scholars to deal with the unique risk factors associated with this method. Traditional qualitative analysis models have stood the test of time, demonstrating a good robustness and wide applicability. However, these models require manual intervention and provide a low evaluation accuracy [19-20]. Modern risk assessment models have significantly improved risk quantification, assessment, and prediction. The advent of artificial intelligence algorithms has led to a notable improvement in their data analysis and mining capabilities [21], resulting in the application of intelligent optimization algorithms combined with evaluation models becoming a research hotspot.

The cloud warehouse financing mode theory represents the theoretical sublimation of the supply chain financing mode as a new financing mode. The practical development of cloud warehouse platforms is progressing rapidly, but theoretical research is lagging behind. In practice, enterprises primarily conduct research on cloud warehouse systems, and the unified standardized model has yet to be fully developed. The potential market environment is still actively being explored. Among the services provided by cloud warehouses, supply chain financial services, which form an important component of the enterprise capital chain, are more important than other warehousing services. Both opportunities and challenges coexist in these services, with existing management experience and theoretical guidance being limited. On the other hand, the WOA has gained significant attention from academics due to its small number of parameters, simplicity, and ease of use. An IWOA was applied to solve the supply chain financial risk assessment model of a cloud warehouse platform, providing a new solution and method for credit risk assessment.

3. Methodology

3.1 KMV model

Credit risk is a primary risk faced by commercial organizations. Effectively evaluating and judging credit risks and providing good advice to managers is important. While significant advancements have been made in China's financial management technology, the technical capabilities for risk quantification and the completeness of historical data remain relatively underdeveloped. The

KMV model is a well-established dynamic model, making it less influenced by subjective factors. Its parameters are straightforward to estimate, and it is capable of accurately obtaining the necessary data, offering both flexibility and timely results. Furthermore, it can comprehensively examine the financial information of listed companies and forecast the likelihood of enterprise default based on the closing price of a stock, reflecting the level of enterprise risk to a certain extent. After comprehensively comparing traditional and modern risk measurement models, we selected the KMV model for further study and modification in the evaluation of supply chain financial risk.

Modern asset-pricing and financial theories form the foundation of the KMV model. The influence of corporate debt structure on corporate default probability shows that the accurate assessment and analysis of business credit risk require the calculation of the default point and default distance [23-24]. The core principle of the KMV model is to estimate the expected default rate, followed by the calculation of corporate assets. This is done by adding the weighted sum of long-term debt, short-term debt, and equity value. The model can not only be adjusted dynamically according to historical data but also has a certain predictability and foresight, being able to reflect the comprehensive expectation of the future credit risk of a company in real time. The precise steps in the working of this model are as follows.

First, the net worth of the liabilities, stock value in the market, and volatility of stock market value are used to compute the value of assets and property worth fluctuations. The Black-Scholes-Merton option pricing model is used to estimate the market value of the equity of an enterprise. Then, the relationship between equity value volatility S_E and asset value volatility S_A is derived by solving a system of simultaneous equations. The unknown variables asset value V_A and asset value volatility S_A , which are required in the KMV model, can be obtained as shown in Eq. 1.

$$\begin{aligned} f(V_A, S_A, D, r, T) &= V_E = V_A \times N(d_1) - e^{-r \times T} \times D \times N(d_2) \\ d_1 &= \frac{\ln(\frac{V_A}{D}) + (r + \frac{S_A^2}{2}) \times T}{S_A \sqrt{T}} \\ d_2 &= d_1 - S_A \sqrt{T} \\ S_E &= \frac{V_A}{V_E} \times N(d_1) S_A \end{aligned} \quad (1)$$

Where V_A is the value of the assets, S_A is the value of the asset volatility, V_E is the market value of equity, S_E is the value of volatility in the stock market, $N(d)$ is the function of the cumulative probability distribution of the normal distribution, r is the risk-free interest rate, T is the debt maturity and D is the book value of debt.

The function $N(d)$ is calculated as shown in Eq. 2.

$$N(d) = \delta^d \frac{1}{\sqrt{2\pi}} e^{-0.5x^2} dx \quad (2)$$

Then, the future value is predicted according to the existing value of the company, and the default point (DPT) is set according to the debt structure of the company. In the KMV model, a default may occur if the corporate debt is close to the market value. Therefore, a comparison between the default point and corporate assets is performed to assess the likelihood of default. If a company's assets surpass the default point, the likelihood of a default event is reduced; if they fall below the default point, the likelihood increases. Through the analysis of massive data related to default events, the KMV model suggests that both short- and long-term liabilities are typically subject to default situations. Consider a case in which the default coefficient is set to (1,0.5). In this case, the default point can be obtained as shown in Eq. 3.

$$DPT = 1'STD + 0.5'LTD \quad (3)$$

The gap between the predetermined point and the anticipated value of the company and the volatility of its asset value, that is, the default distance DD , are calculated together. The default distance is the gap between a company's asset value and its default point, calculated as shown in Eq. 4.

$$DD = \frac{\text{Expected asset value} - \text{default point}}{\text{Expected asset value} \times \text{Asset volatility}} \quad (4)$$

According to Eq. 4, the final default distance is a dimensionless variable that represents the probability of default without considering factors such as the market environment, enterprise size, and future growth. The risk of overdue default is inversely proportional to the default distance. The specific expression for the default distance is given in Eq. 5.

$$DD = \frac{E(V_A) - DPT}{E(V_A)S_A} \quad (5)$$

Finally, the overdue default rate and expected default frequency *EDF* of the enterprise are calculated according to the default distance, and the default risk degree of the enterprise is obtained. The computing company for the expected default frequency is given by Eq. 6.

$$EDF = N(-DD) = 1 - N(DD) \quad (6)$$

The KMV model uses all its massive global default database resources to develop a precise relationship between default probability and default distance. This model provides results that are accurate and consistent with respect to real-world scenarios.

3.2 Improved whale optimization algorithm

In 2016, Mirjalili and Lewis proposed a new swarm intelligence optimization method called the WOA [25]. Whales use a distinctive hunting technique, known as the bubble-net hunting method, which is based on their observed social behavior. The working of the WOA is inspired by the behavior of whales. This technique may be roughly broken down into three stages: a bubble-net attack, surround hunting, and hunting for prey.

The whale surrounds the prey based on its location. Mimicking this, the WOA tries to identify the best search agent based on the location. The selected search agent is employed in the next step. Eq. 7 and Eq. 8 present the mathematical models of the process.

$$\vec{D} = |\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)| \quad (7)$$

where *D* is the individual whale distance vector, *X** is the localized ideal response, *X* is the position vector, *t* is the current number of iterations and *C* is the random number in the range [0,2].

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \quad (8)$$

where *A* is the random number in the range [-2,2]. The mathematical expression for *A* is shown in Eq. 9.

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \quad (9)$$

where *a* is the linear decrease from 2 to 0, *r* is the random vector between [0,1]. The mathematical expression of *C* is shown in Eq. 10.

$$\vec{C} = 2 \cdot \vec{r} \quad (10)$$

Whales also use bubble-net strategies to attack their prey. The corresponding stage in the algorithm include contraction encircling and two spiral updates.

According to Eq. 8, when $-1 < A < 1$, mirroring the change in the position of a group of whales, the search agent moves to the best agent in the new location and contracts.

Eq. 11 describes the way a whale (agent) swims (moves) in a decreasing circle while adopting a spiral path.

$$\vec{X}(t+1) = \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) \quad (11)$$

where *D'* is the distance in vector terms between the agent and the optimal agent in the current location, *b* is the parameter that establishes the logarithmic helix form, and *l* is the random number in [-1,1]. An agent is closest to the resource when *l* = -1, and farthest from the resource when *l* = 1.

In the WOA, spiral renewal behavior and contraction encircling behavior occur simultaneously. Mirjalili and Lewis assumed that when updating the positions of the search agents, there would be a 50 % chance of using either the spiral model or the contraction wrapping process during each iteration of the WOA [24]. The mathematical model of this behavior is described in Eq. 12.

$$\overrightarrow{X(t+1)} = \begin{cases} \overrightarrow{X^*(t)} - \overrightarrow{A} \cdot \overrightarrow{D'} & p < 0.5 \\ \overrightarrow{D'} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*(t)} & p \geq 0.5 \end{cases} \quad (12)$$

where p is the random number between $[0,1]$.

Mirjalili and Lewis (2016) used parameter A to describe the way whales hunt prey. When $|A| > 1$, the search agent is compelled to move toward another randomly chosen agent position. This process is called exploration. When $|A| < 1$, the search agent moves toward the optimal agent in its current location. This process is called development.

Theoretically, the WOA can be regarded as a metaphorical *machine* that optimizes an entire environment. The mathematical model is shown in Eqs. 13 and 14.

$$\overrightarrow{D} = \overrightarrow{C} \cdot \overrightarrow{X_{rand}} - \overrightarrow{X} \quad (13)$$

$$\overrightarrow{X(t+1)} = \overrightarrow{X_{rand}} - \overrightarrow{A} \cdot \overrightarrow{D} \quad (14)$$

where X_{rand} is the position vector for a randomly selected whale.

Being a representative of the swarm intelligence algorithm, the WOA includes a few parameters, has a straightforward algorithmic structure, and is easy to use. It falls under the category of bionic group optimization algorithms, exhibiting an outstanding performance in solving optimization problems. To address the shortcomings of the WOA and its frequent low convergence [26-27], this study proposes improvements to the algorithm from the following three aspects.

The WOA can suffer from getting trapped in local optima, and the algorithm can converge prematurely. It is necessary to balance the gradual convergence of the algorithm and its capacity for global search and overcome its premature convergence. The Gaussian mutation operation was introduced to tackle the slowing of personal evolution and the loss of population diversity. Eq. 15 provides the probability density function of the Gaussian distribution.

$$f(x) = \frac{1}{\sqrt{2ps}} e^{-\frac{(x-m)^2}{2s^2}} \quad (15)$$

where m is the expectation of the Gaussian distribution and s^2 is the variance of the Gaussian distribution. When $m = 0$ and $s = 1$, the distribution follows the conventional Gaussian distribution. The mathematical representations of the WOA improved by Gaussian mutation based on Eqs. 8, 11, and 14 are as follows.

$$\overrightarrow{X(t+1)} = (\overrightarrow{X^*(t)} - \overrightarrow{A} \cdot \overrightarrow{D}) \cdot (1 + k \cdot \text{Gauss}(0,1)) \quad (16)$$

$$\overrightarrow{X(t+1)} = (\overrightarrow{D'} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*(t)}) \cdot (1 + k \cdot \text{Gauss}(0,1)) \quad (17)$$

$$\overrightarrow{X(t+1)} = (\overrightarrow{X_{rand}} - \overrightarrow{A} \cdot \overrightarrow{D}) \cdot (1 + k \cdot \text{Gauss}(0,1)) \quad (18)$$

where k (0,1) is a decreasing random number and $\text{Gauss}(0,1)$ is the standard Gaussian distribution.

Regarding DE, it is a powerful technique for addressing limitations in optimization, and it frequently been used in conjunction with other techniques in a variety of disciplines. The availability of a difference operator can lessen the blindness of the algorithm and speed up the optimization process. In the DE method, individual mutations are achieved by randomly selecting two individuals from the population, scaling their vector differences, and combining them with the vector of the individual to be modified. If the new solution has a higher fitness value than the current optimal solution, it replaces the current one; otherwise, the same solution is kept for the next iteration. Through this mechanism, individuals are guided to search for the optimal solution, accelerating the progress of the algorithm and lowering the likelihood of settling on a local optimal solution. The mechanism of DE correction is expressed in Eq. 19.

$$\overrightarrow{X(t+1)} = \overrightarrow{X_i(t)} + F(\overrightarrow{X_m(t)} - \overrightarrow{X_n(t)}) \quad (19)$$

where $\overrightarrow{X_i}$, $\overrightarrow{X_m}$, $\overrightarrow{X_n}$ are arbitrarily different individuals in the t -th generation population and F is the mutation factor.

The AFSA is an adaptive optimization technique whose working is based on the behavior of fish shoals. An artificial fish looks for the best value among the neighboring fish in its field of vision, avoids overcrowding, and moves in its preferred direction. In the basic WOA, an agent simply encircles its intended target and looks for the necessary resources. Therefore, it can easily collide

or even converge to the local optimal value prematurely. Exploiting the congestion factor and the rear-end collision behavior of the AFSA, premature phenomena can be avoided early in the developmental stages of the algorithm, and the capacity of the algorithm for optimization can be increased. The crowding degree discrimination method is expressed in Eq. 20.

$$Y_{max} / n_f > \delta \times Y_i \quad (20)$$

where Y_{max} are amount of the resources near the ideal place at present, Y_i is the self-state value of the artificial fish (agent), n_f is the number of individual artificial fish (agent) and δ is the congestion factor.

With an increase in the δ size, the capacity for congestion decreases while the ability of the algorithm to escape local optima increases. To avoid overcrowding around extreme values or strong points, the artificial fish (agent) will randomly depart or be rejected by other artificial fish (agent) when approaching such values, resulting in them being unable to precisely locate these values, slowing down the convergence speed of the algorithm. When the inequality holds, the artificial agent will consider the Y_{max} position to be too crowded.

4. IWOA-KMV credit risk assessment model

4.1 Parameter variables

Macroscopically, the enterprise stock market value V_E includes two parts: the market value of the enterprise's tradable shares V_{E1} , and the market value of the enterprise's non-tradable share V_{E2} , that is, the market value of equity V_{E2} , which is given in Eq. 21.

$$V_E = V_{E1} + V_{E2} \quad (21)$$

According to the Merton model, the enterprise stock market value can also be calculated using the company asset value V_A , as given in Eq. 22.

$$V_E = V_A \cdot N(d_1) - e^{-r \cdot T} \cdot D \cdot N(d_2) \quad (22)$$

where V_E is the equity market value, V_A is the cumulative probability distribution function of the asset value, $N(d)$ is the normal distribution variable, r is the risk-free interest rate T , is the debt maturity and D is the debt book value.

According to Ito's lemma, the stock price volatility S_E is given by Eq. 23.

$$S_E = \frac{V_A}{V_E} \cdot N(d_1) \cdot S_A \quad (23)$$

The volatility S_A of the asset values V_A and return on assets can be calculated according to Eq. 23, which represents the stock price volatility S_E .

The book value of the debt of an enterprise can be obtained from financial reports. According to the option pricing theory, when the corporate asset value V_A is close to or less than the corporate debt book value D , the enterprise has a high probability of default risk, otherwise, the probability of default risk is small.

The results of the KMV model after many sample analyses and calculations revealed that when the enterprise asset value V_A was at a certain point between the short-term and total liabilities, the enterprise would default at a point called the default point. In the KMV model, the default point is defined as given in Eq. 24.

$$DPT = 1'STD + 0.5'LTD \quad (24)$$

where the short-term debt STD and long-term debt LTD have been added according to the coefficient combination (1,0.5), and the default trigger point DPT is the standard coefficient configuration of (1,0.5).

Since the thick-tailed distribution of the asset value was different from the actual default of the enterprise, the default distance DD in the KMV model was used to express the distance between the probability distribution of the asset value and the starting point of default and further calculate the expected default rate DEF of the enterprise.

The overdue default rate DEF of an enterprise indicates the possibility of default.

In this study, to facilitate a simple comparison, we chose the one-year time deposit benchmark interest rate of Renminbi (RMB) from the financial institutions of the People's Bank of China in 2019 as 1.50 %. Considering the 90-day treasury bond yield as a risk-free interest rate is a common approach in many financial markets around the world. However, when analyzing the Chinese financial market, it is important to consider the national conditions and the characteristics specific to it.

In the KMV model, the debt maturity of credit risk assessment is usually one year and accurately reflects the current state of short-term liabilities, where $T = 1$.

4.2 Model setting

In the traditional KMV model, the default point is usually calculated as the sum of the short-term debt multiplied by 1 and the long-term debt multiplied by 0.5. To explore the best choice of the default point for the KMV credit risk assessment model, we modified the KMV model and set the default point as the linear sum of the long-term debt multiplied by b and the short-term debt multiplied by a . The IWOA iteratively calculates the optimal combination of the coefficients (a and b) for short-term and long-term debt with the aim of determining the closest approximation to DPT , as shown in Eq. 25.

$$DPT = a'STD + b'LTD \quad (25)$$

An enterprise faces a higher default risk if its estimated asset value is below the default point. In the KMV model, the degree of default risk can be clearly measured through the default distance and default point. Under the general assumption of normal distribution, the default rate can be determined using a probability distribution function. Since there is currently no credible rating agency in China, it is essential to have a single measurement standard for the chosen samples. This study derives conclusions from the assessment of the China Securities Regulatory Commission regarding special treated (ST) shares. The CSRC marks identified listed companies with abnormal conditions and designates them as ST shares to alert investors of potential investment risks. The determination of the optimal default point of the KMV model can be transformed into an optimization problem by considering whether the evaluated enterprise has been categorized as an ST share or non-ST share.

A company with a good credit is considered a good credit company belonging to category G and one with a bad credit is considered a bad credit company belonging to category B. We chose equal amounts of data from companies with and without ST shares. The proportion of samples from firms with and without ST shares was $N/2$.

Since the number of samples of ST and non-ST shares was the same, according to the KMV model, the default distance DD of each company adopted the mean $\overrightarrow{DD}$ as the discriminant criterion; that is, when the default distance DD of the evaluated company was less than or not less than $\overrightarrow{DD}$, the company was judged to be class B or class G, respectively, as shown in Eq. 26.

$$\text{if } \begin{cases} DD \geq \overrightarrow{DD} & \text{the company is judged as a class G company} \\ DD \leq \overrightarrow{DD} & \text{the company is judged as a class B company} \end{cases} \quad (26)$$

Correct classification:

- a. ST share companies are classified as class B
- b. Non-ST share companies are classified as class G

Classification errors:

- c. ST share companies are mistakenly classified as class G
- d. Non-ST share companies are mistakenly classified as class B

The probability of occurrence of the misclassification error m for the mistaken classification of companies with c ST shares as class G is given by Eq. 27.

$$P_1 = 1 - \frac{2m}{N} \quad (27)$$

The probability of occurrence of the misclassification error n for the mistaken classification of companies with d non-ST shares as class B in is given in Eq. 28.

$$P_2 = 1 - \frac{2n}{N} \quad (28)$$

The average misjudgment rate refers to the average probability of misjudgment caused by the two deviation coefficients a and b when the IWOA model is used to calculate the optimal combination of deviation coefficients. The average misjudgment rate is expressed by Eq. 29.

$$f(a, b) = \min \left(1 - \frac{m+n}{N} \right) \quad (29)$$

Fig. 1 illustrates the steps involved in the determination of the optimal default coefficient combination based on the IWOA-KMV model.

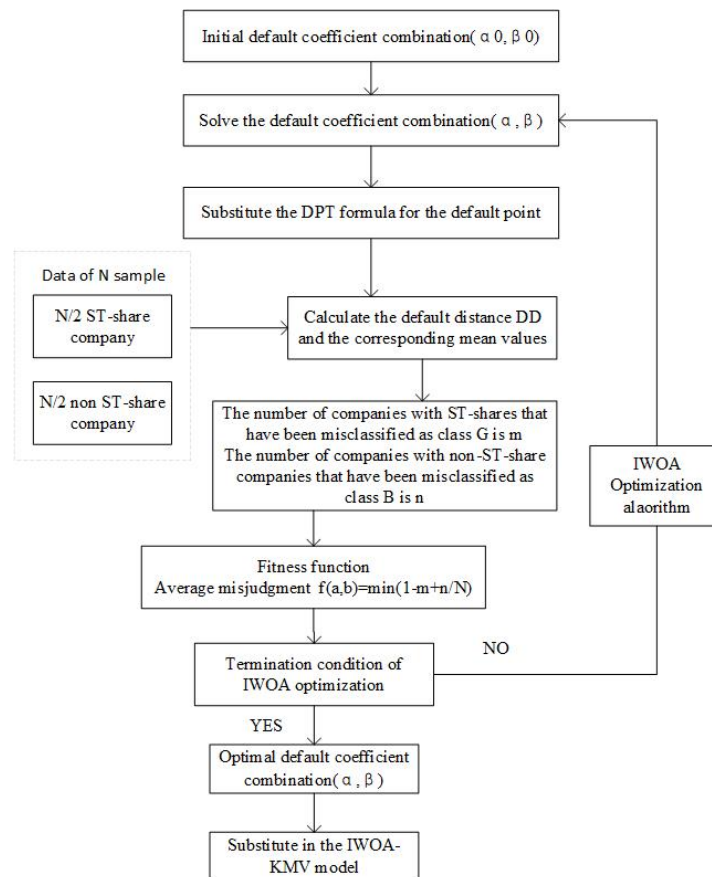


Fig. 1 Steps in the IWOA-KMV model

5. Simulation study on IWOA-KMV credit risk assessment model

5.1 Sample data acquisition and processing

The KMV model was selected to optimize and improve the IWOA-KMV model and assess the credit risk of businesses using real-time data from the capital market, which requires public information. Additionally, considering the challenges involved in gathering data samples and the accessibility of actual business financial data, we selected the data of listed companies as samples to simulate the IWOA-KMV model and verify its effectiveness. The data of risk warning (ST or * ST) companies were selected to conduct model simulation research. The ST or * ST mark indicates that a particular company has sustained a continuous operating loss for 2–3 years, potentially posing a risk of delisting. There are some measures, such as special treatment or a delisting warning, which are used to deal with a listed firm with an * ST designation; such a firm has experienced operating losses for two years in a row or has unusual circumstances, including financial data fraud, which may lead to the risk of delisting. * ST shares indicate a *delisting warning*. Stock exchanges take

special measures to address companies with investment risks, including poor operating conditions and financial anomalies, to provide warnings to investors.

In this study, we selected companies marked as ST and non-ST in the same industry from 2014 to 2019 for data analysis. Then, we determined the default distance and default probability of the two types of businesses using the IWOA-KMV model to assess whether they were consistent with the actual condition of the companies (in terms of the ST designation). The sample was divided into training and testing sets. For the training samples, 150 listed companies classified as ST and 150 companies classified as non-ST from China, covering the years 2014, 2015, and 2016, were selected. These samples were used to calculate the optimal coefficient of the default point. In 2017, 2018, and 2019, 150 Chinese listed companies in China were designated as ST, and the corresponding 150 listed companies in the north (not by ST) were selected as test samples, and the effectiveness of the model was statistically analyzed.

5.2 Model simulation

To explore the best combination of the optimal short-term debt coefficient a and long-term debt coefficient b in the KMV credit risk assessment model and modify the default point to improve the results of the model, the IWOA was utilized in this study to carry out the optimal iteration on the basis of the KMV model and construct the IWOA-KMV calculation model for the optimal default coefficient. Using the idea of optimization to determine the best combination of the optimal short- and long-term debt coefficients (a, b), we modified the default point for the model to obtain better results. The parameter settings of the IWOA and IWOA-KMV are listed in Table 1.

Table 1 IWOA and IWOA-KMV parameter settings

Parameters	Value	Meaning
SearchAgents_no	50	Population size
G	0	Initial number of iterations
Max_iteration	500	Maximum number of iterations
r	1.50 %	Risk-free rate of return
T	1	Debt maturity
(a_0, b_0)	(1,0.5)	Initial default coefficient combination

One hundred and fifty companies in China were listed with ST in 2014, 2015, and 2016. The corresponding unidentified companies (listing status is Norm) were selected as the development samples. The IWOA was applied to 50 iterations of the training samples to calculate the optimal coefficient combination of the default points. Finally, the optimal default coefficient combination of the current liability and long-term liability was obtained in the optimal default point calculation equation, and the ideal short-term debt to long-term liability default coefficient combinations were approximately 3.06 and 1.13, respectively.

The optimal default point of the IWOA-KMV model is calculated as shown in Eq. 30.

$$DPT = 3.06'STD + 1.13'LTD \quad (30)$$

In 2017, 2018, and 2019, 210 Chinese listed firms were chosen as test samples, and the corresponding unidentified companies (listing status is normal) were selected as test samples. The KMV and IWOA-KMV models were used to simulate the test samples. The calculation rules for the default point in the KMV model are given by Eq. 31.

$$DPT = 1'STD + 0.5'LTD \quad (31)$$

The calculation rules for the default points in the IWOA-KMV model are given by Eq. 32.

$$DPT = 3.06'STD + 1.13'LTD \quad (32)$$

To demonstrate the effect of the model correction more intuitively, a double comparison was used to simulate the model.

The default distance DD_{KMV} and $DD_{IWOA-KMV}$ of each enterprise were calculated by using the KMV model and IWOA-KMV model, respectively, to determine the extent of any potential improvements in the measurement accuracy of the default coefficient and whether the IWOA-KMV model had a better discrimination effect than that of the KMV model.

The data of the ST share and non-ST share companies were used for the simulation to verify whether the IWOA-KMV model had a better accuracy than that of the KMV model. The extent of the improvement in the performance of the KMV model through the IWOA could reveal a good distinction between the companies designated as ST (listing status is ST or * ST) and unmarked companies (listing status is Norm), which primarily depicted the amount of disparity between the default distances of the two types of firms, thus proving the goodness-of-fit and measurement performance of the IWOA-KMV model.

5.3 Analysis of simulation results

First, the calculation results of the test sample data were analyzed. The data with no obvious anomalies were marked as correct, and the correctness rate was calculated. A comparison of the correct rate of the default distance under different combinations of the default coefficients used by the KMV and IWOA-KMV models is given in Table 2.

According to the calculation results, the accuracy of the IWOA-KMV model was higher than that of the KMV model for both the ST share and non-ST share companies.

Using the mean difference test of the results of the test samples calculated by the IWOA-KMV model, the default distances under different combinations of the default coefficients used by the KMV and IWOA-KMV models were compared. The results are presented in Table 3.

It is widely known that the probability of the default increases as the default distance decreases. The default probability of the ST companies was higher than that of the norm companies in the calculation findings of the two models, adhering to practical scenarios. Furthermore, the average default distance of the IWOA-KMV model was 1.67, which was much greater than the 1.09 of the KMV model, from the perspective of mean difference. Therefore, based on the optimal default coefficient combination calculated by the IWOA algorithm, it was clear that the IWOA-KMV model and the KMV model had different results, and the default point correction had a better differentiation for the two types of companies with different degrees of risk.

Table 2 Comparison of the correct rates of the default distance under the KMV model and IWOA-KMV model

Name	Model Default coefficient combination	Correct rate of the default distance	
		ST share company (%)	Norm. corp. (%)
KMV	(1,0.5)	95.71	91.90
IWOA-KMV	(3.06, 1.13)	98.10	97.62

Table 3 Comparison of the mean difference of the default distance between the KMV model and IWOA-KMV model

Name	Model Default coefficient combination	Average default distance		Mean difference
		ST company	Norm. corp.	
KMV	(1,0.5)	1.79	2.88	1.09
IWOA-KMV	(3.06, 1.13)	1.54	3.21	1.67

6. Conclusion

Currently, China's cloud warehouse platform model is still in its early stages. The existing literature on cloud warehouse platforms, shared warehousing, and related supply chain financial services is limited, and publicly available data is scarce. Additionally, because the cloud warehouse model does not have a unified standard, there are many types of financial service products, and the links involved in financing risk control are complex. There are certain limitations in our analysis of financial risk in a supply chain using a cloud warehouse platform.

This study presents a thorough analysis of the novel financing model for the cloud warehouse platform from the perspective of the intelligent supply chain finance revolution and provides a preliminary discussion on the current situation and management methods of credit risk assessment using the cloud warehouse financing model. Considering the cloud warehouse platform, this study examines and assesses the financial credit risk associated with the supply chain and conducts an in-depth analysis of the unique individual risk of the operation mode of the cloud warehouse. The evaluation problem was simultaneously transformed into an optimization problem, and the optimization mechanism of the swarm intelligence optimization algorithm was used as a

reference to determine a reasonable default point and default distance. Additionally, the WOA was selected instead of the swarm intelligence optimization algorithm in enhancing the optimization performance of the conventional WOA and handling this problem more effectively. Based on the optimization capabilities of the enhanced algorithm and the analysis of China's credit risk situation, this study proposes the IWOA-KMV model, which is an improvement on the traditional KMV measurement model. This model is a new credit risk measurement method that can support advancements in existing credit risk measurement practices. In the early stage of listing, small and medium-sized enterprises may have a large number of non-tradable shares and imperfect data, and the value of non-tradable shares cannot be directly observed by the market.

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