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Research Article

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Venture financing risk assessment and risk control algorithm for small and medium-sized enterprises in the era of big data

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Abstract: The existing risk assessment and control methods of enterprise risk financing have a large error in mobile data, which leads to inaccurate risk assessment results and low-risk optimization control efficiency. In order to improve the accuracy of risk financing risk assessment for small and medium-sized enterprises (SMEs) and risk control optimization efficiency, this article proposes risk assessment and risk control algorithms for SMEs in the era of big data. Through verifying the information of the loan application and supplementing the data during the loan period, invoke the existing enterprise financing risk database, establish the SME venture financing risk assessment model; build the risk evaluation index system according to the characteristics of the enterprise production organization, process characteristics, and the development of the socioeconomic and technical environment; apply the GA–PSO algorithm to the design of the SME risk financing risk control scheme, and complete the SME risk financing risk assessment and risk control. The experimental results show that the risk optimization control efficiency of the control algorithm reaches more than 70%, and the risk assessment accuracy of SMEs reaches over 95%, and the runtime less than 80 ms, with good convergence performance of risk assessment and control, strong risk optimization control ability, and accurate evaluation effect.

Keywords: entrepreneurship of small and medium-sized enterprises, financing risk, assessment, risk control algorithm

1 Introduction

The financing difficulties of small and medium-sized enterprises (SMEs) are mainly manifested in the shortage of funds caused by the single financing channel of SMEs. Most of the reinvestment funds of enterprises come from profits, and the remaining few sources of funds are mainly loaned from financial institutions [1]. Relevant studies have pointed out that only about 10% of SMEs are mainly funded by loans. From the perspective of borrowers, due to the low cost of capital use, the popular source of loan funds for enterprises is bank loans, but in reality, the vast majority of SMEs cannot smoothly obtain bank loans [2]. The reason is that in the view of banks, SMEs cannot provide enough fixed assets as collateral, so they will not take the risk of approving the credit they need; while in the view of SMEs, banks have strict conditions for collateral, the process of loan approval is too long, and the efficiency is too low to support their sustainable development, so they turn to private fast lending, which has high financing cost and further worsened the cash flow of SMEs [3]. To sum up, the problems of financing difficulties and high financing costs of SMEs restrict the daily operation of SMEs, such as R&D and new projects, and even affect the

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survival of SMEs. Therefore, it is of profound practical significance to explore the new financing mode of SMEs and how to use the latest technology of big data to carry out the risk assessment of SME financing.

At present, for small- and medium-sized science and technology enterprises, the research methods of credit risk assessment are diverse, such as KMV credit measurement model, genetic neural network, etc. On the basis of analyzing the particularity of listed SMEs, Yang used GARCH to modify the KMV model, and uses the optimized KMV credit measurement model to calculate the risk level of enterprises based on some core parameters of the enterprise credit data [4]. However, this method requires a large collection of data, and the screening and processing of these data samples, and the evaluation accuracy is not high; Yan and Meng established an index system by analyzing the factors affecting the financing risk of small and medium-sized technology enterprises, classified as 6 primary risk factor indicators and 18 secondary risk factor indicators [5]. Then, the weighting of each factors was determined by hierarchical analysis Analytic Hierarchy Process and the enterprise financing risk was scored by experts. However, the evaluation results obtained by this method using the hierarchical analysis method alone are often incorrect. Hu et al. proposed a short-term electric load prediction model based on the GA–PSO–BPNN algorithm [6]. The GA–PSO algorithm is applied to the short-term power load prediction model of industrial enterprises to optimize the parameters of the BPNN. The prediction model avoids the disadvantages of the prediction results easily entering the local optimum and achieves the hybrid control of the short-term power load for the two enterprises. However, this method does not predict the financing risk of entrepreneurial venture capital of SMEs. The selection of prediction indicators is not accurate enough and is applied to the investment risk assessment of SMEs, and the accuracy of the assessment results is not high; Sedeh et al. presented a new mathematical model for optimizing the maintenance scheduling problem of multilocation facilities [7]. A combination of genetic algorithms and particle group optimization was used to solve the problem of multi-position asset organization. Consider the differences in specific distances and travel times between multiple locations, outsourcing is compared to the company's own experts, and select the best scheduling scheme. The method focuses on the scheduling of facilities, while the evaluation indicators come from experts in internal and external aspects, but no comprehensive analysis of the indicators, leading to poor evaluation results; Uthayakumar et al. presented a financial crisis prediction model based on ant colony optimization (ACO) [8]. ACO-based feature selection algorithm was used to screen five benchmark datasets from economic and historical data; and data classification algorithm based on ACO was used to further classify the data. Using the classified dataset to build the ACO–FCP integration model of financial crisis prediction, which is more robust, but the prediction results of this method are more biased to the macroeconomic situation, and the accuracy of the prediction results in the venture capital prediction of SMEs is not high. In addition, Du et al. established a network credit risk early warning model based on the BP neural network using a large data sample. Genetic algorithm is used to optimize the neural network and improve the early warning accuracy of Internet Credit [9]. Shao et al. presented an end-to-end multi-objective neuroevolution algorithm (MONEADD) based on decomposition and advantage to solve the combinatorial optimization problem. The MONEADD is an end-to-end algorithm that utilizes genetic manipulations and reward signals to evolve neural networks to address different combinatorial optimization problems without further engineering of the ref. [10]. Zhai combined the principles of principal component analysis, particle group optimization algorithm, and artificial neural network, derived the financial risk index system, applied the algorithm to optimize the BP neural network model, and constructed the BP neural network model [11].

In order to avoid problems of the above methods and improve the accuracy of credit risk assessment and risk control optimization efficiency for SMEs, this article puts forward the risk assessment and risk control algorithm of SMEs in the era of big data. The research process is as follows: through the verification of loan application information and social, economic, and technical environment, dynamically identify the false information of loan enterprises; build a machine learning-based entrepreneurial financing risk assessment model; and adjust the financial risk assessment index system according to the characteristics of the enterprise production organization, process characteristics, and the development status of social, economic, and technical environment. The GA–PSO hybrid planning algorithm is used to establish the optimal credit risk evaluation model for technology-based SMEs to realize risk financing risk assessment and risk control for SMEs. The innovation point of this article is to optimize the financial risk assessment index by using the krill algorithm and the Aquila optimizer to be more accurate; the GA–PSO hybrid planning algorithm was used to analyze the relationship between the enterprise credit evaluation index and the financing credit rating, the enterprise credit rating was roughly divided into five levels, the optimal credit risk evaluation model was established, and the credit risk of SMEs was predicted and evaluated. The experimental results show that this method improved the accuracy of risk financing risk assessment and risk control optimization efficiency of SMEs, which can reliably reduce the financing risk for SMEs, which provides a more explanatory and accurate basis for the risk assessment for SMEs.

2 Construction of venture financing risk assessment model for SMEs in the era of big data

The credit evaluation model includes the verification of SME loan application information and the supplement of various data during the loan period.

(1) Loan application information verification: the rules usually used for modeling include enterprise historical dishonesty data, court execution data, enterprise illegal production data, enterprise tax abnormal data, enterprise product quality complaint information, enterprise executives' personal abnormal data (including identity verification, real name authentication, personal resume fraud, frequent replacement of mobile phone number, and common equipment), no abnormality, whether the common contacts are abnormal and others, etc.

(2) Various data supplement during the loan period: through the tax payment data, customs import and export data, electricity consumption data, logistics and transportation data, bank flow data, business data of upstream and downstream manufacturers, personal information data of enterprise executives, etc. During the operation of SMEs, the sales, production, product quality, and other business situations of enterprises after obtaining loans are mined through machine learning algorithm, information on the changes of senior executives [9].

With the development of the daily operation of SMEs, the in-depth development of various enterprise construction and product R&D projects, the scale and frequency of obtaining financial support are increasing day by day, which will inevitably lead to a large number of loan applications with uneven quality, and the credit risk and the risk of loan fraud by purse companies will increase rapidly [10]. The traditional credit evaluation technology of banks and other financial institutions leads to that they are only willing to deeply cultivate the medium and large enterprises with sufficient collateral and good credit in historical stock. However, if they can use some new, multidimensional data, machine learning, and other novel technical methods for credit evaluation and prediction, the accuracy of default risk prediction of SMEs can be greatly improved [11,12].

Collecting, integrating, excavating, and analyzing all kinds of data in each financing business establish a mathematical model based on the credit rules of SMEs, and dynamically identify the loan enterprise's false industrial and commercial information, quality problem product information, false credit audit materials, false contacts, false office location, false asset information, executive list with court enforcement information, etc. The high-risk loan enterprises are automatically rejected by the system [13,14].

The big data platform automatically adopts different decision-making strategies according to the level of risk. The loan demand with high risk is rejected directly, the loan demand with high risk is reviewed again, the loan demand with low risk is investigated by sampling, and the loan demand with low risk is checked directly through manual inspection [15]. In the whole process, all kinds of labels and data that need further certification are listed in the risk monitoring list and determined manually [16,17]. If such a label does have credit risk problems, the behavior will be included in the risk action model, so that the credit evaluation model is constantly learning and evolving [18]. The machine backstage records and studies each stage of the financing application approval process, including SME information, executives and related data, and calls all kinds of existing enterprise financing risk databases through the engine to build an SME venture financing risk assessment model, as shown in Figure 1.

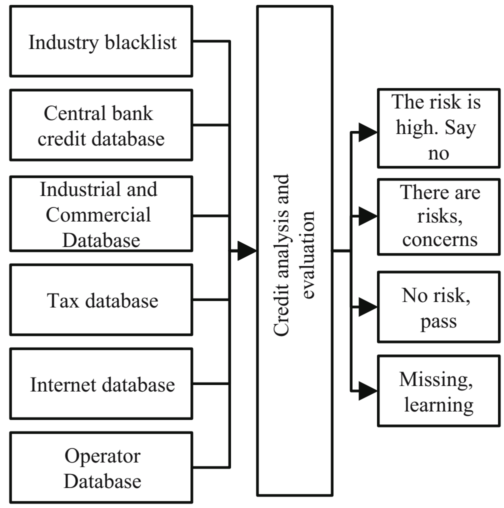

Figure 1: Risk assessment model of venture capital financing for small and medium-sized enterprises.

As can be seen from Figure 1, the above credit evaluation model based on machine learning can be used in the financing application and post loan stage of SMEs. Through active and continuous learning of all kinds of risk information, it can respond to all kinds of emerging loan fraud, enterprise operation risk, and other information that will affect the loan in a flexible mode, improve the credit risk evaluation ability of the model, and prevent and eliminate the risk of loan funds [19].

3 Construction of risk assessment index system

In order to evaluate financial risk comprehensively and systematically, enterprises should not only set up special financial risk evaluation department, but also employ accounting talents with high comprehensive quality. According to the enterprise's production organization characteristics, process characteristics, and the development status of social economic and technological environment, the old financial risk evaluation index system is improved, and the newly constructed risk evaluation index system is shown in Figure 2.

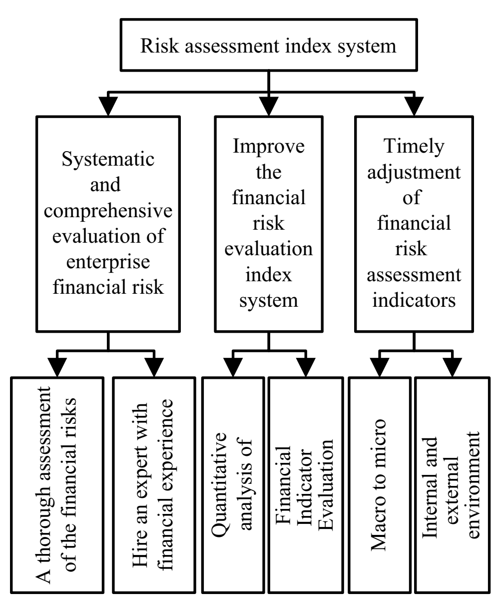

Figure 2: Risk assessment index system.

As shown in Figure 2, with the help of big data and cloud computing technology to analyze financial data, we can find opportunities or threats hidden behind the data, make the static data "live," and fully explore its value. In order to more accurately evaluate the financial risk of enterprises, through the analysis of the deficiencies in the financial risk evaluation of enterprises in China, combined with the characteristics of financial risk in the era of big data, a set of more perfect enterprise financial risk evaluation index system is constructed [20–22].

(1) Systematic and comprehensive evaluation of enterprise financial risk

With the rapid development of the global economy, the business environment faced by enterprises is becoming more and more competitive, and the influencing factors of enterprise financial risk are becoming more and more complex. This not only requires enterprise managers to pay more attention to financial risk evaluation and establish financial risk awareness, but also requires enterprise managers to systematically and comprehensively evaluate the financial risk they are facing, and be able to manage it reasonably. We should deal with it. When using the financial risk evaluation index to implement the evaluation, we should not only see the influence of a specific index on a certain aspect of the enterprise, but also see the role of the relevance between multiple different indexes in the production and operation of the enterprise. In addition, for large and medium-sized enterprises with strong financial strength, it is suggested to employ experts with rich financial experience to carry out financial risk assessment from the overall strategic perspective.

(2) Improving the financial risk evaluation index system

Most of the existing financial risk evaluation index systems focus on quantitative analysis and evaluation of financial indicators, and pay less attention to qualitative research and the role of non-financial indicators. However, these two aspects cannot be ignored to correctly understand the threats faced by enterprises. Therefore, in the implementation of financial risk assessment, enterprises should add some nonfinancial indicators that have an important impact on the enterprise, and make appropriate qualitative analysis. Only by combining these aspects can the financial risk evaluation index system be more complete.

(3) Timely adjustment of financial risk evaluation index

With the continuous development of enterprises, the financial risk and technical environment are constantly changing, which requires enterprises to adjust the financial risk evaluation index system in a timely manner, so as to ensure that the financial risk evaluation results are more accurate and help enterprises make more effective strategic decisions. Under the background of big data era, enterprises are facing new financial risks, such as data concentration risk, hacker Trojan horse attack on data system, and other illegal intrusion risks. The impact of these risks on enterprises is likely to be fatal. Therefore, when implementing financial risk assessment, enterprises should make corresponding adjustments according to the development and changes of macro and micro, internal and external environment, so as to give better play to the important role of financial risk assessment and help enterprises find risks and find countermeasures as soon as possible.

The financial risk assessment indicators were optimized using Krill Herd Algorithm. The Krill Herd Algorithm, based on the foraging properties of krill populations, was first proposed in 2012. The principle of Krill Herd Algorithm is that krill populations constantly assemble to increase population density and reduce the chance of predation while exploring living areas, shortening their distance from food as much as possible, and ultimately giving the population access to food.

The Krill Herd Algorithm was optimized using Aquila Optimizer by the following steps:

(1) Defines boundaries and determines the algorithm parameters (evaluation index scale N_{p}, maximum number of iterations $t_{\max}$, maximum induction speed $N_{\max}$, maximum foraging speed $V_{\max}$, maximum random diffusion speed $D_{\max}$, induced inertia weight W_n, foraging inertia weight W_{f}, and step scaling factor t, etc.).
(2) Randomly generates initial financial risk assessment metrics in the Aquila Optimizer search space.
(3) Evaluates each metric based on the sequence of the index (the adaptive value function is calculated/optimizes the objective function calculation).

(4) Velocity components were calculated, and the weights were calculated for the training speed.
(5) Multi-index adopts cross-operation to determine the weight.
(6) Updates the index sequence within the Aquila Optimizer optimal indicator search space.
(7) Returns to step 3 until the stop condition is met (maximum iterations $t_{\max}$).

Krill Herd Algorithm and Aquila Optimizer are used to optimize financial risk assessment indicators.

4 Venture financing risk control algorithm based on GA–PSO algorithm

Based on GA–PSO hybrid programming algorithm, this article constructs an optimal evaluation model of credit risk of small and medium-sized science and technology enterprises. The main steps are as follows: first, select certain small and medium-sized science and technology enterprises, and select some enterprises with accurate and reliable credit rating as assessed by the evaluation institution; second, select some indicators that can reflect the operation ability and debt repayment ability of SMEs; third, select some indicators that can reflect the operation ability and debt repayment ability of SMEs. The relationship between the evaluation index and financing credit rating of technology-based SMEs is explored by GA–PSO hybrid programming algorithm, and its credit risk rating is predicted and evaluated. The basic function expression is as follows:

$$C = f(x), \tag{1}$$

where $C = [1, 2, 3, 4, 5]^T$ represents the credit risk level of technology-based SMEs. According to the theoretical research of enterprise credit risk rating evaluation model, the credit rating is roughly divided into 5 levels, expressed with 1, 2, 3, 4, 5. The specific meaning is as follows:
(1) It means that small and medium-sized technology-based enterprises have sufficient ability to cope with the current debt, can deal with the sudden debt crisis outside, and have good credit status, so they can pay off the loan immediately.
(2) It indicates that technology-based SMEs can provide security for their debt situation, timely respond to external sudden debt crisis through internal turnover, have good credit status, and repay loans through internal turnover.
(3) It means that small and medium-sized technology-based enterprises have a certain degree of security for the current debt. In the long run, there is a certain degree of instability, but through their own efforts, they can repay the loan.
(4) It means that there is a certain credit risk in the debt situation of technology-based medium and low-end enterprises. Although they have the willingness to repay, their ability to repay is limited.
(5) It indicates that the technology-based SMEs are not willing to repay their debts, and their repayment ability is low and their credit risk level is high.

x is the index of technology content, debt repayment ability, and operation status of technology-based SMEs:

$$X = [x_1, x_2, \cdots, x_n]^T, x_1, x_2, \cdots, x_n, \tag{2}$$

where T represents the specific index value, and exploring the relationship between C and X is the ultimate goal of the model construction, that is to find the specific form of f. Under the support of the algorithm, the risk control scheme of SME venture financing is designed.

5 The design of venture financing risk control scheme for SMEs

In order to reduce the financing risk of start-up enterprises, it is necessary to choose the financing channel suitable for start-up enterprises according to their own conditions and market environment, so as to effectively avoid and control the risk.

5.1 Finance lease

Financial leasing, also known as equipment leasing or modern leasing, refers to the leasing that transfers all or most of the risks and rewards related to the ownership of assets. The ownership of assets can be transferred or not. According to the specific requirements of the lessee and the choice of the supplier, the lessor invests in the purchase of the leased object from the supplier and rents it to the lessee. The lessee pays the rent to the lessor by stages. During the lease term, the ownership of the leased object belongs to the lessor, and the lessee has the right to use the leased object.

At the end of the lease term, after the rent has been paid and the lessee has fulfilled all the obligations in accordance with the provisions of the financial leasing contract, the ownership of the leased object shall be transferred to the lessee. Although in the financial leasing transaction, the lessor also has the identity of equipment buyer, the substantial contents of purchasing equipment, such as the selection of suppliers, the specific requirements for equipment, the negotiation of purchase contract conditions, are enjoyed and exercised by the lessee, and the lessee is the substantial buyer of the leased items. Financial leasing is a new type of financial industry, which integrates financing and financing, trade and technology update. Due to the characteristics of the combination of financing and financing, the leasing company can recover and deal with the leased property when there is a problem. Therefore, the requirements for enterprise credit and guarantee are not high when handling the financing, which is very suitable for the financing of start-up enterprises. In addition, financial leasing belongs to off balance sheet financing, which is not reflected in the liability items in the financial statements of enterprises, and does not affect the credit status of enterprises, which is very beneficial for start-up enterprises that need multichannel financing.

5.2 Risk investment

Venture capital is a new way of financing and investment, which is a new thing in China. Entrepreneurs can get a sum of money by selling part of their shares to venture investors. Venture capital investors bear the risk of whether the enterprise can develop. Therefore, start-ups do not have to worry about whether they can repay the venture capital. That is to say, venture capital is a kind of capital that can be borrowed without repayment. Venture capital is a special way of investment, compared with the traditional investment cycle is longer, generally 3–5 years. In addition, venture capital basically invests in the fields that traditional investors dare not or do not want to get involved in, especially start-up enterprises. Therefore, for start-ups, venture capital has a special irreplaceable role, and it is also one of the superior financing channels and one of the most direct financing methods in the financing process.

First of all, newly started enterprises need equity capital financing in particular. The expansion of venture capital is largely reflected in the early financing of new ventures. The newly started enterprises especially need equity capital financing. If they rely too much on loan financing, they are likely to be crushed by the debt burden before they get a lot of profits and break through the “bottleneck” in the early stage of development. At the same time, early-stage financing is exactly where venture capitalists need to use coaching technology to manage their investment. Therefore, venture capital is the essence of venture capital.

Second, there are many benefits for start-ups accepting venture capital. The company has no debt burden, does not worry about losing the controlling right, and the venture capital has formed "rules of the game," which generally exits within 3–5 years, and the equity in the holding period only accounts for about 10%. There is no need for assets as collateral; at the same time, we can get other help and avoid detours. Venture capital companies often Coach Enterprises in finance, management, and marketing to avoid unnecessary failure and loss due to lack of experience.

5.3 Special loans

Bank financing is the main source of funds for start-up enterprises at this stage. In addition to the traditional liquidity loans, start-up enterprises generally lack collateral, there are also the following special loans:

Joint cooperative loans in other places: some start-ups have a wide market for their products, or they provide supporting parts for some large enterprises, or they are loose subsidiaries of enterprise groups. In the process of producing cooperative products, they need to supplement production funds. They can seek a leading bank to provide loans to the group companies, and then the group companies provide necessary funds to the cooperative enterprises. Local banks cooperate in contract supervision. It can also be combined by the leading bank and the deposit bank of the cooperative enterprise in different places to provide loans separately. Intellectual property pledge loan: intellectual property pledge loan refers to the application for financing from the bank after the property rights in the legally owned patent right, trademark right, and copyright have been assessed. Some high-tech start-ups can apply to the bank for project development loans if they have significant value transformation projects of scientific and technological achievements, the initial investment amount is relatively large, and the enterprise's own capital cannot bear it. For high-tech start-up enterprises that have established stable project development relationship with colleges and universities and scientific research institutions or own their own research departments, banks cannot only provide working capital loans, but also handle project development loans.

6 Case analysis

In order to verify the rationality of the risk assessment and risk control algorithms of SMEs in the era of big data, this article uses an example analysis.

6.1 Case background

In this study, 64 technology-based SMEs were randomly selected from the SME sector of Shenzhen stock market in 2014 as the credit risk assessment samples, including 10 test samples and 54 training samples, amount to 660 M data. An evaluation team composed of financial directors of financial institutions, managers of industry competent departments, and university experts and professors of relevant majors evaluate the credit rating of the selected enterprises and obtain the determined y value. At the same time, the annual reports of the 64 enterprises released at the end of 2014 were standardized according to the standardized way.

6.2 Data analysis and model checking

The model analysis process is divided into the test part and the training part. In the training part, 54 enterprises in the loan repayment period are randomly selected from 64 sample enterprises. By using Yang [4] method, Yan and Meng [5] method, and designed method of this article, the enterprise credit risk evaluation model was established in the experimental configuration shown in Table 1.

Table 1: Experimental configuration

Serial number	Software and hardware environment	Configuration
1	Operating system	Windows10
2	Development Platform	JetBrains PyCharm
3	CPU	Intel (R) Core (TM)
4	RAM	16G
5	Development language	Python3.7

The calculation results are compared from the aspects of convergence, optimize efficiency, and accuracy. Convergence is the number of training times to obtain the advantageous results, which reflects the optimization ability of the algorithm. Convergence and optimization efficiency are both indicators of the optimization performance of the algorithm. Results on both indicators can be evaluated by accuracy test and running time test.

In the three methods of comparing the curves, X-axis represents cycle, unit time is s; Y-axis represents average fitness, running ten times. It can be seen from Figure 3 that the convergence performance of designed method is better than that of Yang [4] method, and it is obviously faster than that of Yan and Meng [5] method. This is because the risk assessment index system of this method is more systematic and comprehensive, which can use the GA–PSO mixed planning algorithm to adjust the financial risk assessment index in time. Therefore, the convergence performance is excellent, the convergence speed is fast, and it can deal with different risk assessment enterprises.

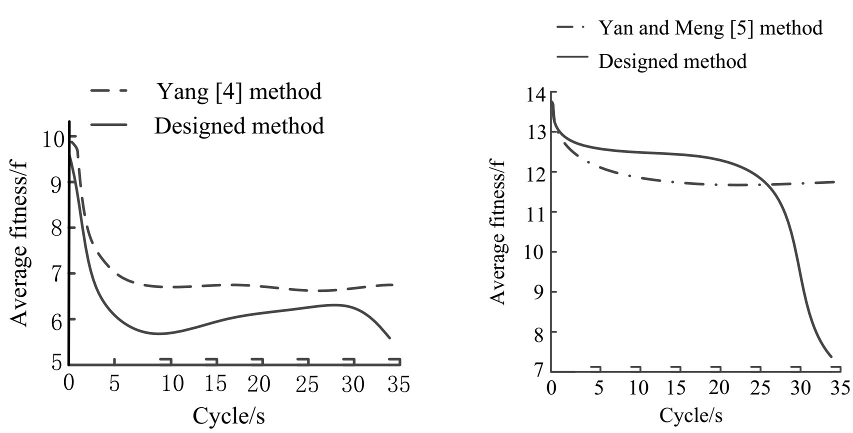

Figure 3: Performance comparison of three methods.

Based on the research of convergence and accuracy of designed method, five groups of index values of 64 science and technology-based SMEs are processed and analyzed in MATLAB R2014a environment, and the results are shown in Figure 4.

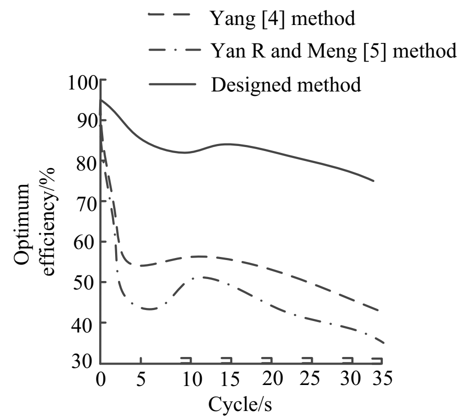

Figure 4: Comparison of three models.

It can be seen from Figure 4 that the optimization efficiency of designed method has reached more than 70%, which is higher than Yang [4] method and Yan and Meng [5] method. This is because the GA–PSO hybrid programming algorithm has minimal fitness convergence in the same environment, indicating a distinct diversity of particle groups and thus a strong local optimization power. Based on this algorithm, the optimal enterprise credit risk evaluation model can optimize risk parameters and control of risk optimization.

Based on this, three methods are used to compare the accuracy of risk assessment, and the comparison results are shown in Table 2.

Table 2: Comparison of accuracy of three risk assessment methods

Experiment times/time	Yang [4] method	Yan and Meng [5] method	Designed method
1	0.61	0.82	0.98
2	0.60	0.81	0.97
3	0.59	0.85	0.97
4	0.58	0.87	0.96
5	0.57	0.80	0.95
6	0.57	0.81	0.96
7	0.58	0.85	0.97
8	0.59	0.79	0.98
9	0.55	0.78	0.97
10	0.57	0.78	0.97

As shown in Table 2, the risk assessment accuracy of designed method is above 95%, significantly higher than the other two methods. This is because this article first uses the krill group algorithm and the Aquila optimizer to optimize the financial risk assessment index, improve the accuracy of the evaluation index, and lay the foundation for the accuracy of the evaluation. The optimal credit risk evaluation model of technology-based SMEs based on the GA–PSO hybrid planning algorithm was established. By analyzing the relationship between the SME evaluation index and the financing credit rating, the optimal results of the risk evaluation are obtained through continuous iteration, with high accuracy.

Dividing 660M data into six datasets, three methods are used to compare runtime for the different datasets, and the comparison results are shown in Figure 5.

According to Figure 5, as the amount of data increases, the running time of all three methods begins to increase, among which the running time of the present design method is less than 80 ms, with the shortest running time and the highest running efficiency. This is because the GA–PSO hybrid planning algorithm

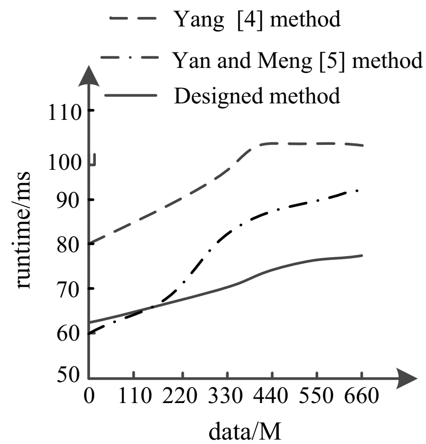

Figure 5: Comparison of three methods.

used in this article can converge to the optimal solution faster than the evolved individual in other individual algorithms.

7 Conclusion

In order to improve the accuracy of credit risk assessment and control for SMEs, this article studies the credit risk assessment, and proposes the risk assessment and risk control algorithm for SMEs in the era of big data. Build machine learning-based SME risk financing risk assessment model based on loan application information and data during the loan period, adjust and optimize financial risk assessment index using Krill Herd Algorithm and Aquila Optimizer, improve financial risk assessment index system, use GA–PSO mixed planning algorithm, analyze the relationship between enterprise credit evaluation index and financing credit rating, build the optimal evaluation model for technology SMEs, evaluate credit risk, and put forward strategies for risk control. The results show that the GA–PSO hybrid programming algorithm can effectively predict the credit risk of SMEs. It is better than the other two methods in the convergence of the model, and it is more accurate in predicting the degree of risk. The proposed method improves the accuracy of credit risk assessment and risk control optimization efficiency for SMEs. It can not only improve the local optimal characteristics of the enterprise, but also optimize the enterprise credit risk assessment model as a whole. According to the design method of this article, enterprises can change the financial risk evaluation system, accurately evaluate and judge the enterprise's financial risks, enhance the enterprise value, better develop and expand the enterprise, and win a higher market share.

However, due to limited conditions, the research in this article is limited to credit risk assessment for SMEs, no risk assessment for large enterprises with more credit data, and future research can further improve the broad applicability of evaluation methods.

Conflict of interest: Author states no conflict of interest.

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