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Design of Financial Indicator Analysis System Based on Fuzzy Recognition Algorithm and Big Data

Tianyi Yao[1,✉]

[1.] Changchun Finance College, Changchun, Jilin, 130000, China

ABSTRACT

Financial analysis is a method of analyzing the overall operating status of an enterprise based on financial information, which can help managers judge the company' s operating risks and adjust the company' s operating conditions in a timely manner, so as to better achieve business management. This paper aims to study the design of financial indicator analysis system through big data. This paper proposes to find the best clustering center by means of fuzzy identification algorithm, determine the quality of the company' s operating status, calculate the company' s overall operating indicators, and determine the company' s risk level and improvement direction. The experimental results of this paper show that the fuzzy identification algorithm can help the enterprise to determine the overall state of the enterprise' s operation, improve the financial risk identification ability by 20%, and better realize the enterprise' s financial analysis and processing.

Keywords: Fuzzy Recognition Algorithm, Big Data, Financial Indicator Analysis System, Clustering Algorithm

1. Introduction

Financial analysis is a financial management activity based on accounting information such as enterprise financial reports, using a series of analytical methods and indicators, research and evaluation of the enterprise's financial position and operating results, and providing a basis for economic forecasting or decision-making for investors, business managers, creditors and other sectors of society [1-3]. It is both the summary of the completed financial activities, but also the premise of financial forecasting, in the financial management cycle plays an important role in the beginning and end [4-6]. At present, the financial software used by enterprises, whether simple financial accounting software or large ERP management software is a series of economic activities such as purchasing, production, sales, inventory control and management, and can not make conclusive analysis and judgment of the financial situation, business conditions [7-9]. Therefore, both operators, creditors and people from all walks of life, economic forecasting or decision-making is

✉ Corresponding author.
E-mail address: ccjrtyt@163.com (T. Yao).
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generally done through professionals to make manual financial analysis before making decisions. This is also one of the main job responsibilities of financial executives. Simply put, at present it is difficult for most non-financial professionals to make reasonable financial decisions based on statements without manual analysis reports from professionals [10-13]. In recent years, in the study of financial indicator systems, how to extract valuable information from a large number of financial indicators and analyze them in depth, so as to build a perfect financial indicator analysis system has become an urgent problem in the economic field [14-16]. The integration of fuzzy recognition algorithm and big data into the process of financial indicator analysis, combined with the actual decision-making analysis needs of enterprises to design a financial indicator analysis system on the SAPBW platform, which can extract effective information from a large number of financial indicators, and can make judgments and early warnings on the company's situation according to the results of the analysis, and provide a scientific basis for decision-making for business leaders [17-20].

This paper selects financial indicators from different angles, establishes a systematic and comprehensive financial indicator analysis system, finds the best clustering center through fuzzy identification algorithm, and judges the overall operation status of the enterprise and the problems faced by the current operation, so as to realize the optimal decision-making of the enterprise to help enterprises avoid related risks.

2. Introduction to Big Data and Fuzzy Recognition Algorithm Principles

2.1. Fuzzy Recognition Algorithm

2.1.1. Fuzzy sets. Fuzziness comes from the ambiguity that is common in lives. Fuzzy set, as the name suggests, is a set in a fuzzy state, which has uncertainty. In traditional set theory, an element a either belongs to set B, denoted as $a \in B$, or does not belong to set B, denoted as $a \notin B$, which is a hard set. In the characteristic function, for the set B, its characteristic function $f_B(a)$ can be written as:

$$f_B(a)=\begin{cases}1, a \in B \\ 0, a \notin B\end{cases} \tag{1}$$

For fuzzy sets, each element belongs to a certain set to a certain extent, or belongs to multiple sets to a certain extent at the same time. The different trends of intermediate things are generally described by membership functions. The membership function can be expressed as $L_B(a)$, and can think of membership functions as extensions of feature functions in traditional sets.

On the space $K=\{k\}$, the fuzzy set $\widehat{B}$ is its membership function. In $k_1, k_2, \ldots, k_n$, fuzzy set $\widehat{B}$ can be expressed as:

$$\widehat{B}=\{(L_B(k), k_n) | k_n \in K\} \tag{2}$$

$$0 \leq L_B(k) \leq 1 \tag{3}$$

As the value of $L_B(k)$ approaches 1, the higher the degree of membership of element k is, and vice versa. The relationship between membership and fuzzy sets is shown in Figure 1:

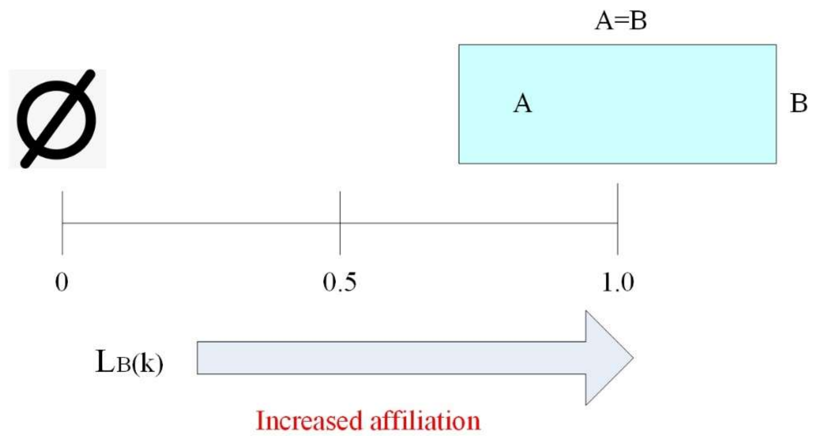


Fig. 1. Evaluation concept of fuzzy membership

In the clustering problem, the cluster can be regarded as a fuzzy set. Therefore, the membership of each sample point to the class is a value in the closed interval [0,1].

2.1.2. Fuzzy clustering theory. Cluster analysis is the whole process of obtaining useful knowledge from data by means of computational methods on the basis of data mining. It can be used to obtain data distribution status and summarize data classification characteristics, as shown in Figure 2. Cluster analysis is a formal research method and algorithm for grouping or grouping objects based on intrinsic characteristics or measured or perceived similarity. Generally speaking, the similarity of the same cluster is higher than that of different clusters, which is the basis for cluster distinction. But many problems in life mostly involve higher-dimensional clustering, which is difficult to distinguish with the naked eye, so a standard is needed to measure the clustering process.

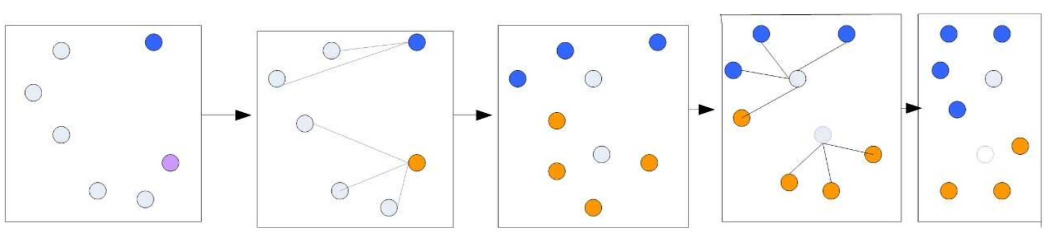


Fig. 2. Schematic diagram of data clustering process

Cluster analysis requires input samples, which have n unknown categories, such as $y_1, y_2, \ldots, y_n$, which can be represented by ordinal pairs (Y, a) or (X, b). a and b are standard parameters, respectively, used to measure the similarity or difference between samples. The output result of the clustering system is the divided data, that is, $J = \{J_1, J_2, \ldots, J_n\}$, $J_a(a = 1,2,\ldots,n)$ is a subset of J and satisfies the following conditions:

$$\begin{cases} J_1 \cup J_2 \cup J_3 \cup \ldots \cup J_n = J \\ J_p \cap J_q = \Phi, \forall p \neq q \end{cases} \tag{4}$$

A clustered subset of J can be denoted as $J_1, J_2, \ldots, J_n$, which contains multiple features. Clustering is the most common way of representing clusters by their centers, which is a good way when clusters are compact or isotropic, but it does not represent them correctly when classes are elongated or isotropic.

Similarity is the basis for defining clustering, but for clustering algorithms, the clustering criterion of samples is more about measuring the distance in the feature space, rather than directly calculating the similarity of samples. For the sample space, a metric or a near metric is generally used to represent the value of the distance of the sample, which is used to measure the diverse samples.

The two samples b_1 and b_2 in the sample space are represented by $x(b_1, b_2)$. When b_1 and b_2 are highly similar, the value of $x(b_1, b_2)$ is very large, and when b_1 and b_2 are very different, the value of $x(b_1, b_2)$ is very small. Moreover, the similarity x has symmetry:

$$x(b_1, b_2) = x(b_2, b_1) \tag{5}$$

Dissimilarity is also called distance, which is used more as a criterion. The dissimilarity $d(b_1, b_2)$ is used to represent. When the difference between b_1 and b_2 is small, the value of the distance from $d(b_1, b_2)$ is small. When the difference between b_1 and b_2 is very high, $d(b_1, b_2)$ is very large. Similarly, dissimilarity also has symmetry:

$$d(b_1, b_2) = d(b_2, b_1) \tag{6}$$

The most commonly used distance measurement methods are Minkowski distance, Markov distance and Cosine distance.

1) Minkowski distance. Letting the feature dimension be i and the feature denoted as e, f. Its Minkowski distance metric can be expressed as:

$$d(e, f) = \sum_{x=1}^{m} \left(|e_x - f_x|^r \right)^{1/r}, r > 0 \tag{7}$$

When the value of r is different, it can represent different distances. $r = 1$, the Minkowski distance is the absolute value distance:

$$d(e, f) = \sum_{x=1}^{m} |e_x - f_x| \tag{8}$$

$r = 2$, the Minkowski distance is the Euclidean distance.

$$d(e, f) = \sqrt{\sum_{x=1}^{m} (e_x - f_x)^2} \tag{9}$$

2) Mahalanobis distance. Letting G be a sample population drawn from a parent J with mean γ and covariance $\sum x$, and the Mahalanobis distance from sample g_x to sample population G is:

$$d^2(g_x, G) = (g_x - \gamma)^T \sum_x^{-1} (g_x - \gamma) \tag{10}$$

3) Cosine distance (Cosine). In cluster analysis, vectors in n-dimensional space are used to represent objects, and $J_x = (J_{x1}, J_{x2}, \ldots, J_{xn})^T$ is the x-th object. Their similarity coefficient can be represented by the cosine of the angle between the two vectors, that is:

$$F_{xy} = \cos(\omega_{xy}) = \frac{\sum_{i=1}^{m} j_{xi} j_{yi}}{\sqrt{\sum_{i=1}^{m} j_{xi}^2 \sum_{i=1}^{m} j_{ji}^2}} \tag{11}$$

The same classification standard may produce different clustering classification methods. According to the degree of membership, clustering can be divided into traditional clustering and fuzzy clustering. The difference between the two lies in whether the boundaries of the clusters are clear. In life, the boundaries of objects are not obvious, so fuzzy clustering is more applicable. Fuzzy clustering expands the scope of clustering. Although the uncertainty of objects is higher, the clustering effect is better, the output results are more accurate, and the actual classification effect can be better displayed.

$M=\{m_1,m_2,\dots,m_Z\}$ is a given data set, which is a finite set of observed samples, derived from a database of Z-patterns in pattern space. m_x is an e-dimensional feature vector or pattern vector. The data set M is divided into f classes of $\{R_1,R_2,\dots,R_f\}$. If the membership function is used to represent the membership relationship between the sample m_x and the subset R_i, it is obviously for the hard clustering $\gamma_{xi}\in\{0,1\}$, the fuzzy set theory extends the membership function γ_{xi} through the binary value {0,1} at the interval [0,1], so that the matrix formed by the values of the eigenfunctions of the subset F can be expressed as $W=[\gamma_{xi}]_{Z*f}$: The fuzzy space of partition F of m is:

$$S_{af}=\left\{W\in H^{fm}\middle|\gamma_{xi}\in[0,1],\forall x,y;\sum_{i=1}^{f}\gamma_{xi}=1,\forall x;0<\sum_{x=1}^{T}\gamma_{xi}<T,\forall i\right\} \tag{12}$$

The objective function of fuzzy clustering is a generalization of the objective function of hard clustering by the concept of fuzzy partition, and the objective function is extended to the weighted sum of squares of objective functions in the class:

$$\begin{cases} Q(W,E)=\sum_{i=1}^{f}\sum_{x=1}^{T}\gamma_{xi}^{p}d_{xi}^{2} \\ s.t.W\in S_{af} \end{cases} \tag{13}$$

Among them, $p\in[1,\infty]$ is the weighted index, also known as the smoothing parameter. In the formula, d_{xi} represents the distortion distance between the sample m_x and the prototype vector s_i in the i-th class, and its general expression can be defined as

$$d_{xi}^{2}=\|m_x-s_i\|C(m_x-s_i)^{T}C(m_x-s_i) \tag{14}$$

The symmetric positive definite matrix of order $a\times a$ is denoted by C. When C takes the identity matrix, the formula corresponds to the Euclidean distance.

For fuzzy clustering, the clustering criterion is to take the minimum value of $Q(W,E)$ $\min\{Q(W,E)\}$, since each column in matrix W is independent, so

$$\min\{Q(W,E)\}=\min\left\{\sum_{i=1}^{f}\sum_{x=1}^{T}\gamma_{xi}^{p}d_{xi}^{2}\right\}=\sum_{x=1}^{T}\min\left\{\sum_{i=1}^{f}\gamma_{xi}^{p}d_{xi}^{2}\right\} \tag{15}$$

According to $\sum_{i=1}^{f}\gamma_{xi}=1$, using Lagrangian multiplication to solve

$$V=\sum_{i=1}^{f}\gamma_{xi}^{p}d_{xi}^{2}+\beta\left(\sum_{i=1}^{f}\gamma_{xi}-1\right) \tag{16}$$

The first-order necessary condition for optimization is

$$\frac{\partial V}{\partial\beta}=\left(\sum_{i=1}^{f}\gamma_{xi}-1\right)=0 \tag{17}$$

$$\frac{\partial F}{\partial\gamma_{xi}}=p\gamma_{xi}^{p-1}d_{xi}^{2}-\beta=0 \tag{18}$$

According to formula (18), getting

$$\gamma_{xi} = \left[\frac{\beta}{pd_{xi}^2}\right]^{\frac{1}{p-1}} \tag{19}$$

Substituting the formula into (17) to get

$$\sum_{i=1}^{f}\gamma_{xi} = \sum_{i=1}^{f}\left(\frac{\beta}{p}\right)^{\frac{1}{p-1}}\left(d_{xi}^2\right)^{\frac{-1}{p-1}} \tag{20}$$

Therefore

$$\left(\frac{\beta}{p}\right)^{\frac{1}{p-1}} = \frac{1}{\left\{\sum_{x=1}^{m}\left(d_{xi}^2\right)^{\frac{-1}{p-1}}\right\}} \tag{21}$$

Substituting the formula into formula (19) to get

$$\gamma_{xi} = \frac{1}{\sum_{y=1}^{f}\left[\frac{d_{xi}}{d_{xy}}\right]^{\frac{2}{p-1}}} \tag{22}$$

Since the distortion distance d_{xi} between the sample m_x and the prototype vector s_i in the i -th class may be 0, the set X_b and $\overline{X}_b$ are defined, and for $\forall b$ there are, $X_b = \{i | 1 \le i \le f, d_{xi} = 0\}$, $\overline{X}_b = \{1,2,\ldots,f\} - X_b$, then the value of γ_{xi} that minimizes $Q(W,E)$ for

$$\begin{cases} \gamma_{xi} = \dfrac{1}{\sum_{y=1}^{f}\left[\frac{d_{xi}}{d_{xy}}\right]^{\frac{2}{p-1}}} \\ \gamma_{xi} = 0, \forall i \in \overline{X}_b, \sum_{i\in \overline{X}_b}\gamma_{xi} = 1 \end{cases} \tag{23}$$

A similar method can be used to obtain the value of s_i when $Q(W,E)$ is the minimum value. Making

$$\frac{\partial}{\partial s_i}Q(W,E) = 0 \tag{24}$$

Getting

$$\sum_{x=1}^{T}\gamma_{xi}^{p}\frac{\partial}{\partial s_i}\left[(m_x - s_i)^T C(m_x - s_i)\right] = 0 \tag{25}$$

$$\sum_{x=1}^{T}\gamma_{xi}^{p}\left[-2C(m_x - s_i)\right] = 0 \tag{26}$$

$$\sum_{x=1}^{T}\gamma_{xi}^{p}\left[-2C(m_x - s_i)\right] = 0 \tag{27}$$

It is obtained from this

$$s_i = \frac{\sum_{x=1}^{T} \gamma_{xi}^{p} m_x}{\sum_{x=1}^{T} \gamma_{xi}^{p}} \tag{28}$$

If the data set M, cluster classes f and weights q are known, then the optimal fuzzy classification matrix and cluster centers can be determined according to an iterative algorithm.

2.2. Big Data

In recent years, with the rapid development of the Internet society, a large amount of information has been digitized, and big data has emerged as the times require. Modern people are all surrounded by this massive amount of data, as shown in Figure 3. The most notable feature of big data is its huge amount of data. The common computer storage unit of measurement has developed from GB to TB, PB, EB, ZB, YB, etc. Today, the industry usually uses “5 Vs” to structure the basic concepts of big data, namely Volume (large data magnitude), Velocity (efficient computing processing), Variety (variety of data types), Veracity (the data source of the letter), Value (the associated data value). It can be seen that big data is a complex and huge data system, not a simple large-scale data collection.

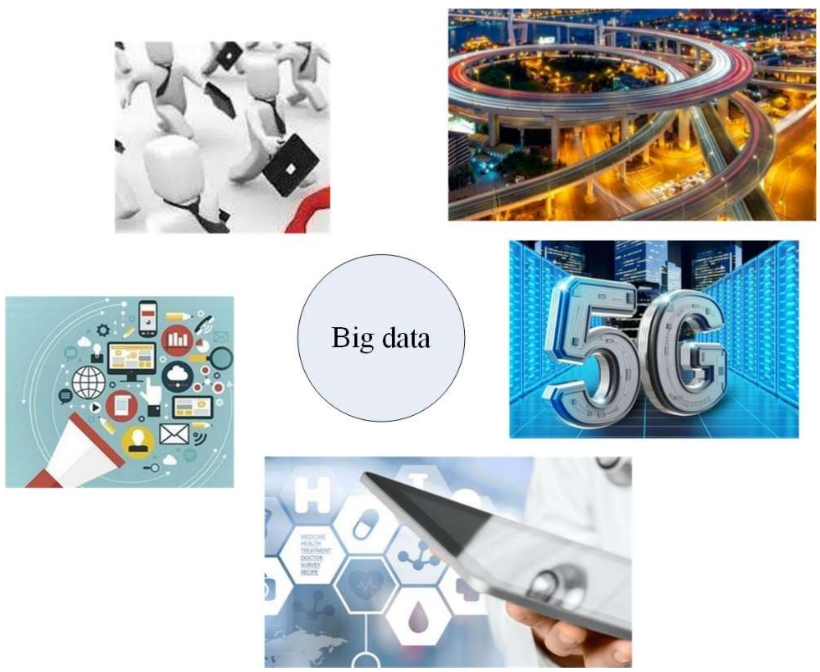


Fig. 3. Big data application scenario

There is no doubt that big data has enormous value. The information mined from big data can help people make better decisions. Compared with traditional data, big data has five characteristics: massive, high-speed, multi-type, low authenticity, and high value. But big data also presents challenges. The main difficulty in dealing with big data is not only its massiveness, after all, alleviating this problem by rationally scaling IT systems. In fact, the real challenges of dealing with big data mainly lie in the diversity of data types, fast response to requests, and data uncertainty. Due to the diversity of data types, applications often need to deal with traditional structured, semi-structured and unstructured data (such as text, images, video, and sound). Real-time response is also challenging as there may not be enough resources to collect, store, and process big data in a reasonable amount of time. Finally, distinguishing between true and false or reliable from unreliable data is a major challenge for even the best data cleaning techniques that clean up some of the inherent unpredictability of data.

3. Construction and Design of Financial Index Analysis System

3.1. System Building Principles

The establishment of the financial analysis index system mainly follows the following principles:
1) The objective principle means that the content described by the index system is objective. It reveals the operating conditions of the enterprise based on the current situation, structure and risk of corporate financing, and provides relevant judgment standards for further decision-making of the enterprise.
2) The system principle means that the index system includes all indicators, which can systematically describe the relevant content of enterprise financing and operation, show the overall financial status of the enterprise, and better evaluate the overall operation and future development direction of the enterprise.
3) The principle of comparability, as the name suggests, means that all evaluation indicators can be compared, and the operating conditions of different enterprises can be compared horizontally and vertically.
4) The principle of utility means that the indicators selected by the indicator system should be reasonable and effective, the indicators should not be repeated, and the indicators should be reasonable indicators to measure the business operation.
5) The principle of efficiency means that the indicators of the indicator system should be calculated reasonably, which can quickly reflect the financial status of the enterprise, and have a general judgment on the operation of the enterprise in a timely manner, so that the system operation is more efficient.
6) The scientific principle means that the design of the indicator system should be scientific, which can accurately reflect the financial status of the enterprise.

3.1.1. Selection of financial indicator groups. There are many indicators involved in the financial comprehensive evaluation. This paper selects the following candidate indicator groups:

Development capability: net profit growth rate, major company revenue growth rate, total asset expansion rate, accounts receivable growth rate, capital investment expansion rate.

Operating capacity: accounts receivable turnover ratio, accounts payable turnover ratio, current asset turnover ratio, total asset turnover ratio, inventory turnover ratio, and fixed asset turnover ratio.

Cash capacity: main business cash ratio, cash self-sufficiency ratio, operating cash flow per share, cash dividend payout ratio, ratio of capital expenditure to operating cash flow.

Profitability: return on net assets, earnings per share, profit margins of main business, profit margins on total assets, profit margins on costs and expenses.

Solvency: gearing ratio, shareholders' equity ratio, current ratio, ratio of net cash flow from operating activities to current liabilities, quick ratio, cash ratio.

3.1.2. Construction of indicator system. This paper selects 30 listed companies in the non-ferrous metal industry in Shanghai and Shenzhen as the samples of the relevant data of the indicator group in 2021. The data source is the original data of securities network star. In order to avoid the influence of the size and magnitude of the rating indicators, it is generally necessary to normalize the data using the following normalization formula:

$$b_{xy} = \frac{c_{xy} - \bar{c}_y}{a_y}, \quad \bar{c}_y = \frac{1}{m}\sum_{x=1}^{m} c_{xy}, \quad a_y^2 = \frac{1}{m}\sum_{x=1}^{m}\left(c_{xy} - \bar{c}_y\right)^2 \tag{29}$$

For index screening, this paper adopts a dynamic screening method combining fuzzy clustering and nonparametric verification, proceed as follows:

1) Dividing the main indicators into groups according to the corresponding conceptual elements, and g_m represents the number of conceptual elements.

2) $g_m = 1$, the concept element is the only optional indicator.

3) $g_m > 1$, indicating that the distribution of indicators is uneven, and it is necessary to rely on non-parametric tests to determine the differences between indicators. If the difference is not significant, the maximum sum of squares of the corresponding indicators should be calculated. If the difference is large, going back to step 1) to divide into smaller categories.

4) $g_m = 2$, when there is no significant difference in the indicators, the square sum of the correlation coefficients of the indicators can be calculated to determine the target indicator. The new financial indicator system is a set of indicators selected from all conceptual elements.

According to the operations, the clustering process is described by taking the cluster analysis of profit index groups as an example. As shown in Table 1:

Table 1. Profitability clustering results

case	clusters
Profit margin of main business	1
Return on net assets	1
Earnings per share	2
Profit margin of total assets	1
Cost profit margin	1

Two types of clustering results can be obtained by using SPSS, and a nonparametric test of multiple independent samples is performed on the indicators in the first type. The results are shown in Table 2:

Table 2. Non-parametric test results of category Ⅰ indicators

	difference
Chi-square	60.394
df	3
Asymp.Sig.	0.037

Since the result of the significance test between indicators is 0.037, which is less than the significance level of 0.05, the indicators in the first category are significantly different and turning to step 3, and then clustering the first category into smaller categories, as shown in Table 3:

Table 3. Profitability category Ⅰ re-clustering results

case	clusters
Profit margin of main business	1
Return on net assets	1

Profit margin of total assets	2
Cost profit margin	2

Going to step 3, checking the class I, the results are shown in Table 4:

Table 4. Non-parametric test results of category Ⅰ indicators

	difference
Chi-square	50.231
df	1
Asymp.Sig.	0.063

Obviously, the result is greater than the significance level, so the index difference in category I is not significant. By calculating the sum of squares of correlation coefficients, whichever is the largest, finally choosing ROE as one of the index systems. In the same way, type II is tested, and the results are shown in Table 5:

Table 5. Non-parametric test results of category II indicators

	difference
Chi-square	0.088
df	1
Asymp.Sig.	0.769

As shown in the table, the difference of the second type of indicators is not significant. By calculating the sum of squares of the correlation coefficients, it can be seen that the largest one is taken, and finally the cost-benefit ratio is selected as one of the indicator systems. Moreover, there is only one indicator in the second category to obtain interest rates, so this indicator is directly incorporated into the indicator system.

Therefore, through the calculation and analysis, it can be seen that the indicators reflecting the company' s profitability can be reduced in terms of ROE, EPS and cost-benefit ratio. Other indicators are calculated according to the methods. To sum up, fuzzy cluster analysis allows the selection of indicators that can be used to construct a financial valuation indicator system for listed companies in the non-ferrous metal industry. The system is divided into five systems, and the specific components are shown in Figure 4:

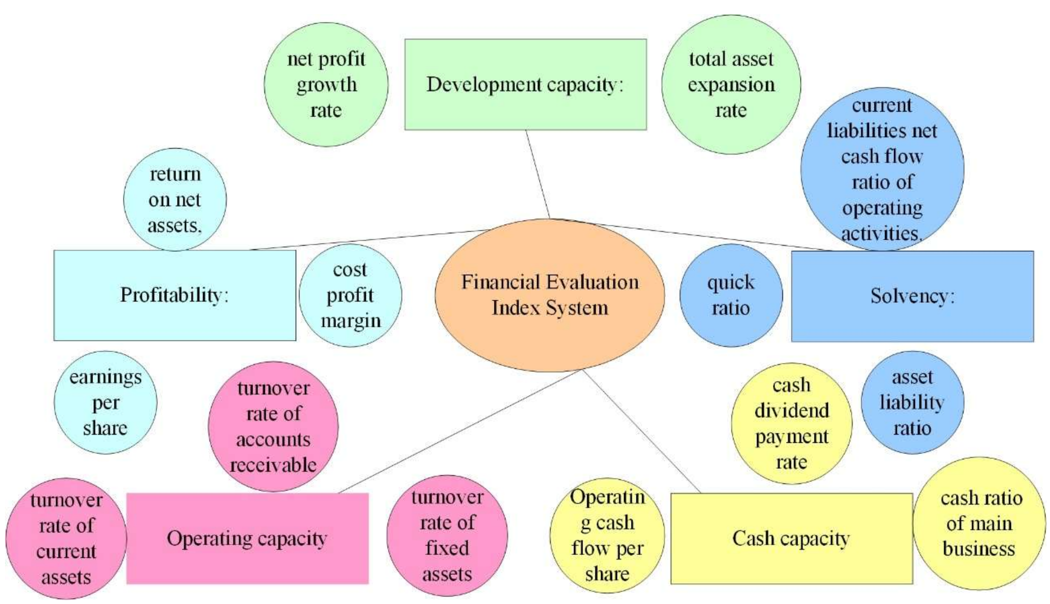


Fig. 4. Structure of financial index evaluation system

3.1.3. Structural design of financial index analysis system. The functions of the financial analysis system mainly include current financial status analysis and financial risk assessment. In order to meet these two functions, the system needs other modules to support, such as database processing module, cache module and linq operation module, of which linq is mainly for data management. It is divided into two parts according to the function, namely the financial risk early warning module and the financial current situation assessment module. The system can be divided into three parts according to the application angle, the financial system setting part, the authority management part and the financial evaluation part. According to the system module, it can be divided into cache module, database module, Excel module (export function), authority module, financial risk warning module and financial current status assessment module. The financial indicator analysis system of this paper belongs to the current financial status analysis module, including data collection, data indicator analysis, output report, etc., as shown in Figure 5.

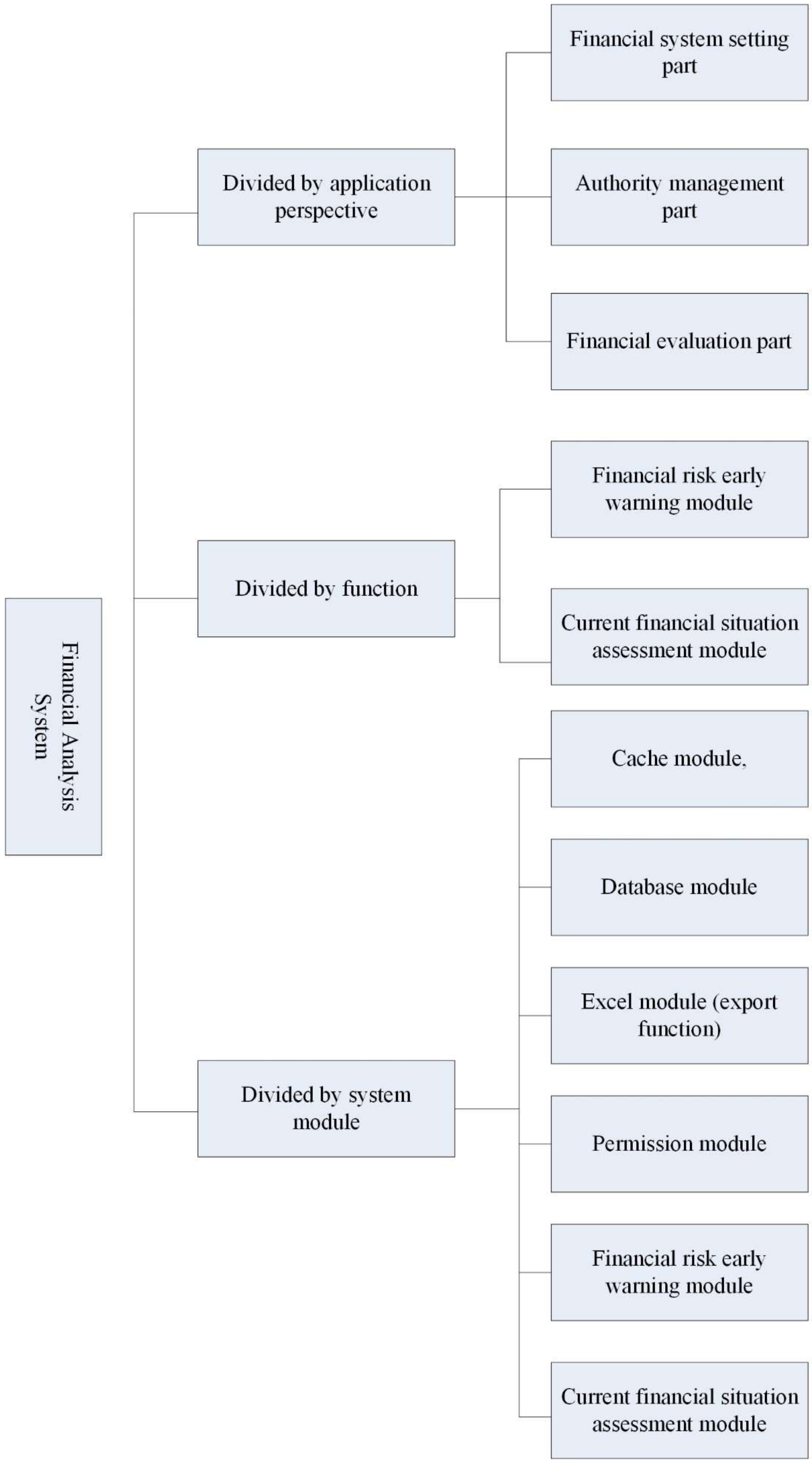
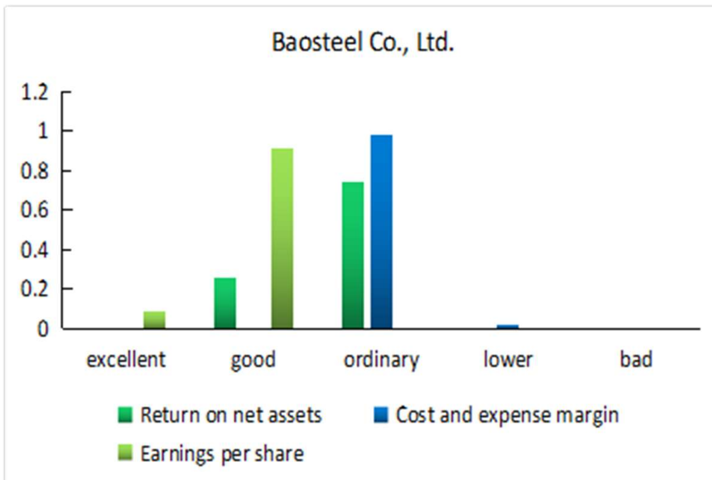


Fig. 5. Financial analysis system structure

3.2. Data Analysis

The financial index is rated on five levels: excellent, good, fair, poor, and poor. Firstly, a hierarchical system is established, and then a judgment matrix is established according to the affiliation between relevant parameters. Based on the data calculated by the judgment matrix, the maximum eigenroot and eigenvector of arbitrary precision are obtained. Calculating the weight of each indicator according to the eigenvector, constructing the membership function of the indicator to determine the membership matrix, judging the level of the company, and determining the overall operating status of the company. This paper selects the financial data of 30 companies on the Securities Star website as a sample to compare the financial status of different companies. This article will select Baosteel (600019) and Valin Iron and Steel (000932) for benchmarking. The membership matrix of the five-level financial indicators of two companies can be obtained by rigidizing without adding any number of financial indicators.

As far as profitability is concerned, it has three evaluation indicators, namely, cost and expense profit margin, return on equity, and earnings per share. As shown in Figure 6, there is a big difference in the evaluation of different indicators of the two companies at different levels. Most of the profitability indicators of Baosteel and Valin Steel are concentrated in two grades of good and medium, but Baosteel' s stock profit is higher than that of Valin.



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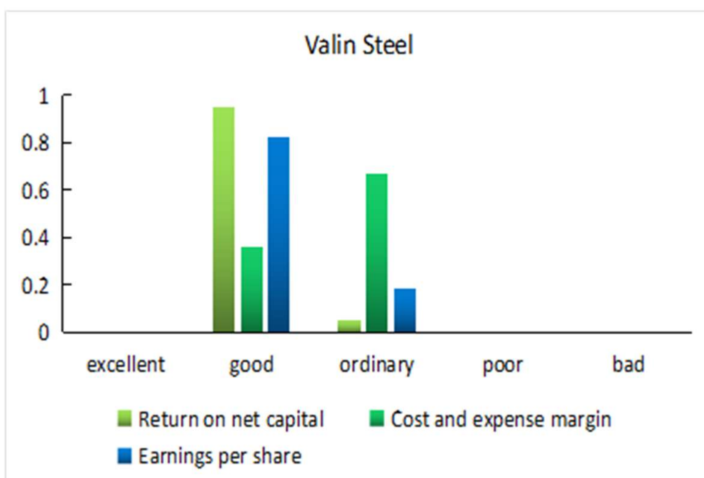
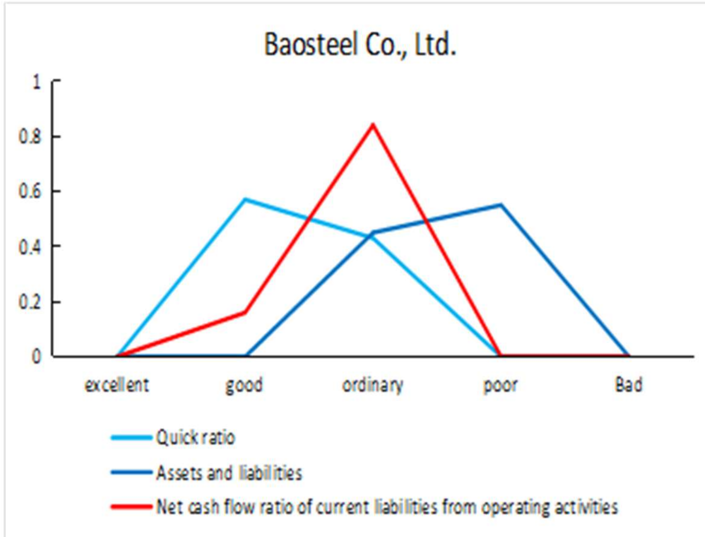


(b)

Fig. 6. Comparison of corporate profitability indicators

In terms of solvency, it includes three indicators: asset-liability ratio, quick ratio, and net cash flow ratio from current liabilities and operating activities. As shown in Figure 7, Baosteel' s solvency is concentrated in two grades: good and medium, and some indicators have poor grades. In general, Valin' s solvency is better than Baosteel' s, showing lower financial risk.



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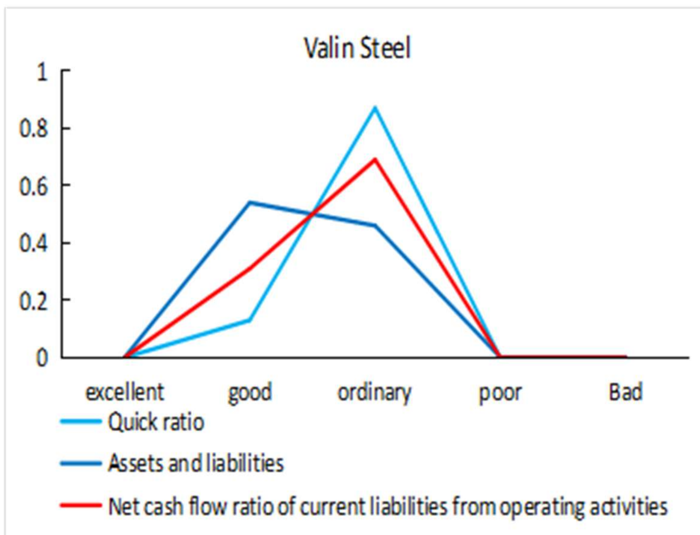
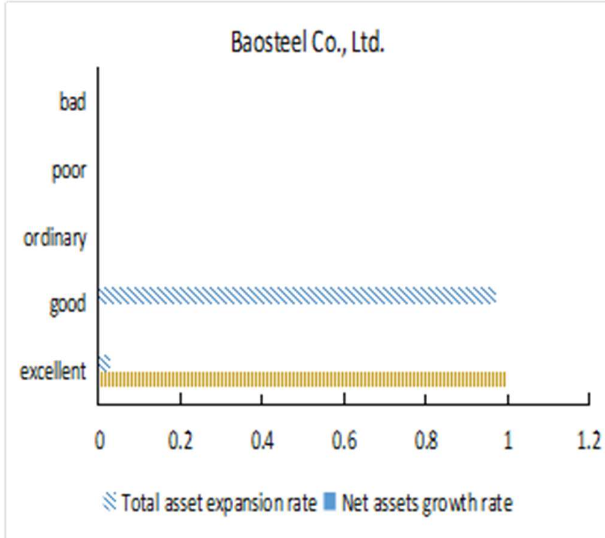


(b)

Fig. 7. Comparison of corporate solvency indicators

In terms of development capability, the two indicators of total asset expansion rate and net profit growth rate reflect the future prospects of the two companies. As shown in Figure 8, the future development prospects of Baosteel and Valin are very good, especially Baosteel' s excellent performance in net profit growth, the overall development of the company is very good, and it is expected to further expand and develop in the future. Although Valin has performed well, it is still slightly inferior to Baosteel.



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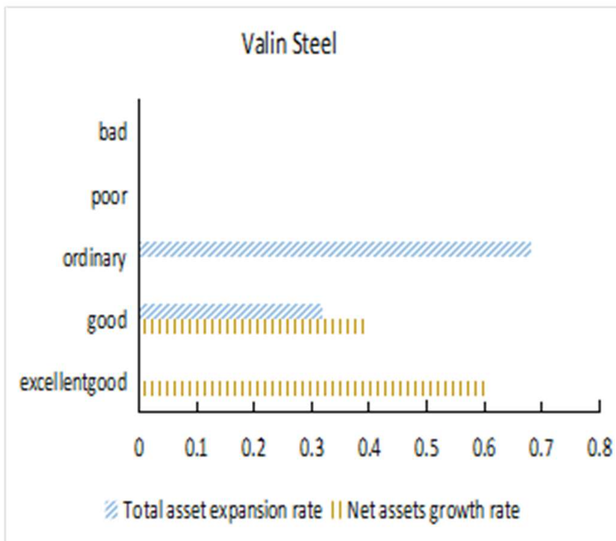
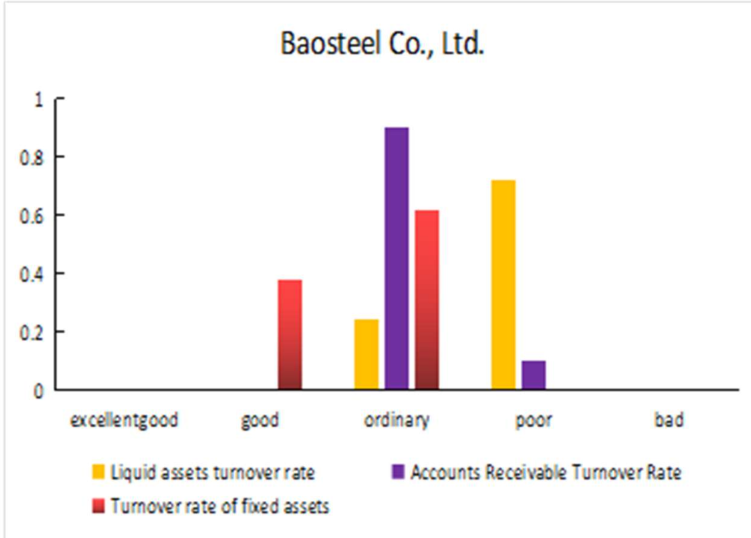


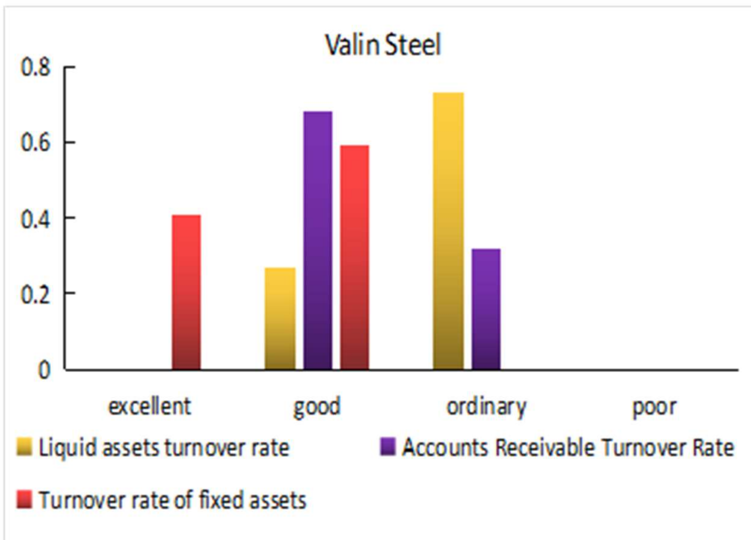
(b)

Fig. 8. Comparison of corporate development capability indicators

In terms of operating capacity, it mainly depends on three indicators: accounts receivable turnover ratio, fixed asset turnover ratio and current asset turnover ratio. As shown in Figure 9, Baosteel' s fixed assets turnover is poor, and accounts receivable turnover is average. In general, Baosteel' s operational capability is not as good as Valin' s. In case of crisis, Baosteel' s capital turnover may be problematic.



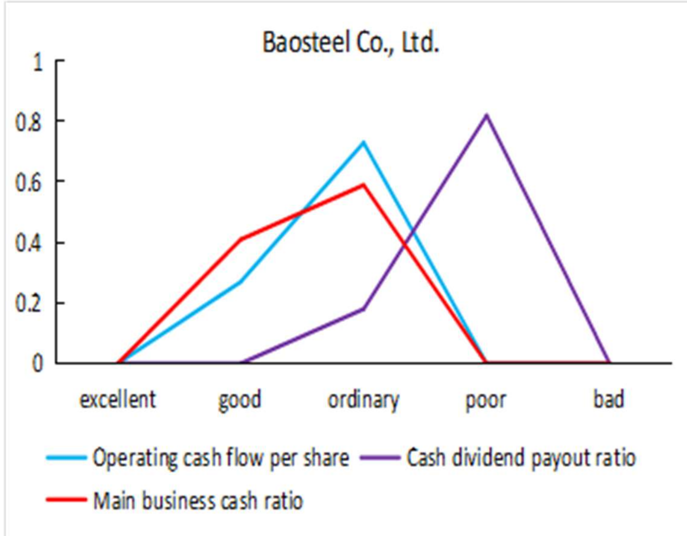
(a)



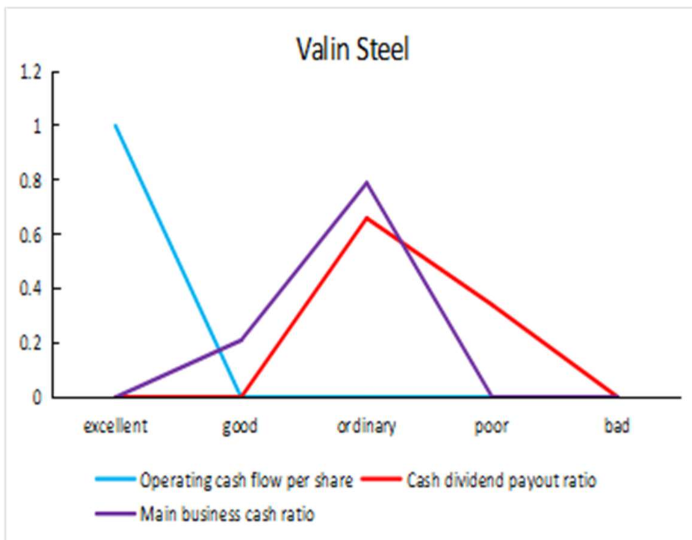
(b)

Fig. 9. Comparison of corporate operating capability indicators

In terms of cash flow capacity, as shown in Figure 10, looking at the three indicators of cash dividend payout ratio, main business cash ratio, and operating cash flow per share, Valin relies more on online sales, while Baosteel takes into account the online sales. Online and offline sales channels. Baosteel' s income has a higher proportion of cash, and Valin' s income may have other factors. Combined with the actual operation of the enterprise, it is found that the difference between the data reported by the financial indicators and the actual data of the enterprise operation is small, indicating that the financial indicator report can be a good measure of the operation status of the enterprise.



(a)



(b)

Fig. 10. Comparison of corporate cash capability indicators

4. Discussion

The experiment constructs the membership degree matrix of the financial indicators of the two enterprises to the five levels. As can be seen from the figure, the profitability and development capabilities of the two companies in the same industry have performed well, and they are promising industries for the future. However, the development direction of the two companies is different. One company is more online development, so its solvency and operating capabilities are good, and its capital turnover is easy. Another enterprise is both online and offline. Affected by the decline of the real industry, there are certain problems in its turnover, so its solvency and operating ability are poor. However, with the support of the national policy to the real industry, in the future, offline enterprises will also gain vitality.

5. Conclusion

With the improvement of enterprise management level and the intensification of market competition, financial indicator analysis, as an important part of financial analysis, has become an important part of company management. This paper designs a financial index analysis system based on fuzzy identification algorithm, using the information value of big data mining, through fuzzy theory to calculate the adhesion matrix of the company’ s financial indicators, to judge the development level of the company, and to comprehensively judge the financial indicators of the company, the overall situation of enterprise operation and management, and to make plans for the further development of the enterprise. However, this paper also has many shortcomings. For example, different analysis indicators are used in different stages of different industries, but this research does not take into account the period in which the company is located. The financial indicator weights and off-balance sheet factors calculated in this article do not apply under any circumstances. This paper choose the indicator group design experience and do not add non-financial indicators, which may have the problem of low accuracy.

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