Publication Date: 31 July 2024 Archs Sci. (2024) Volume 74, Issue 4 Pages 35-43, Paper ID 2024406. https://doi.org/10.62227/as/74406

Analysis of the Role of Economic Management in Enterprise Management in the Context of the Information Age

Chong Wang^{1,*}

¹School of Finance, Henan Institute of Economics and Trade, Zhengzhou, Henan, 450000, China Corresponding authors: (e-mail: ilauralaura@163.com).

Abstract In this paper, the PCNN model is used to reduce the noise of massive enterprise financial data, and the automatic adaptive domain selection method is introduced to complete the dimensionality reduction of enterprise financial data. Based on the clustering algorithm to accurately classify enterprise financial data, combined with the advantages of PSO algorithm to optimize the feature set and kernel function parameters to improve the prediction accuracy of the SVM model, and construct the enterprise financial indicators according to the established PSO-SVM. Analyze the assets and operating profits of the sample enterprise, screen the financial indicators according to the established PSO-SVM model, and calculate the weights and warning intervals of each indicator. Combine the existing data to analyze the economic warning state of the enterprise, and implement enterprise management in combination with financial and economic conditions. Comprehensive leverage of the index weight of 0.0049 \pm 0.0011, and early warning index of 12.793681 > 1.51, seriously out of the normal range, the company's managers need to strengthen the management of the enterprise. The economic and financial management using information technology can promote the benign development of enterprises.

Index Terms PCNN model, PSO-SVM model, clustering algorithm, enterprise management

I. Introduction

n the process of business development, enterprises should keep abreast of the changes in the market environment to ensure that correct decisions are made [1], [2]. By carrying out economic management work, enterprises can better understand their own situation, improve market sensitivity, and ensure the timeliness and accuracy of decision-making [3], [4]. Moreover, economic management can also reflect the profitability of the enterprise, so that the enterprise can formulate a scientific sales strategy after comprehensively analyzing the actual profitability [5]. Enterprises with poor profitability should be investigated and analyzed in detail to clarify the specific reasons and formulate improvement measures [6]. In addition, economic management can also reflect the enterprise's debt situation, based on different debt capacity, choose the corresponding solution measures, also help enterprises to formulate scientific strategic decisions and realize sustainable development [7].

Enterprise economic management is the enterprise combined with the actual organization of a variety of economic activities, through rational planning, scientific layout and coordination of various aspects, to promote the enterprise to obtain the maximum economic benefits [8], and to ensure that the social benefits of the simultaneous enhancement. With the change of the market economy mode, the economic management mode also changes, gradually from the economic management around the production to the production and operation of comprehensive economic management direction change. Under this premise, the enterprise through the rational allocation of resources, cost control and other means to ensure that the production, service and other activities are carried out in an orderly manner, and then continue to improve economic efficiency [9]. In the new economic situation, the changes in the core content of enterprise economic management make it show instructive, comprehensive and relevant characteristics.

Enterprise economic management needs to achieve effective planning, organization, control and coordination of economic activities, requiring enterprises to have flexibility and adaptability in the business process [10], and be able to respond to changes in the market environment in a timely and effective manner. And flexible management is precisely in order to realize this flexibility and adaptability and produce a kind of management. Therefore, enterprise economic management puts forward requirements for the implementation of flexible management, which requires enterprises to improve the flexibility and adaptability of the organization through flexible management to better respond to changes in the market environment [11].

Literature [12] points out that different institutional environments tend to produce their own organizational arrangements to manage their employees, so it is important to understand this type of business management. Literature [13] showed experimentally that management education has a positive effect on cognitive empathy but decreases affective empathy and general empathy. In addition, management programs bring cognitive empathy and affective empathy to a balanced level required for a competitive business environment. Literature [14] builds on this discussion by emphasizing the continuing value of an economics foundation to the entrepreneurship research agenda. Literature [15] advances the field of business management and employee welfare in terms of the individual dimension of CSR, which not only raises the economic efficiency of the business but also improves the welfare of the employees. Literature [16] explored the relationship between customer concentration and corporate sustainable innovation, and how this relationship changes with economic policy uncertainty, and the results show that there is a significant inverted "U" shaped relationship between customer concentration and corporate sustainable innovation. Literature [17] establishes the benefits of corporate recycling models and green management, and its findings can reduce costs, help companies fulfill their corporate social responsibility, increase brand value, and generate the benefits expected from other corporate follow-ups. Literature [18] states that corporate management is a process of constantly striving to achieve one or more goals and balancing the level of capital within a company. The point of balance between the six capitals of the enterprise simultaneously implies the maximum benefit of the enterprise.

Big data drives enterprise economic management in the information age, and economic management combined with big data analysis technology affects enterprise management decisions. This paper utilizes PCNN model to denoise enterprise financial data, chooses automatic adaptation field selection method to process the denoised financial data, and completes the preprocessing of enterprise financial data. The K-means clustering algorithm is used to divide the enterprise financial data, and then the PSO-SVM prediction model is proposed for the early warning of enterprise financial crisis. Select a suitable sample company and analyze the company's assets and liabilities as well as operating profits. The PSO-SVM model is used to screen the financial indicators and calculate the weights of each indicator, and the warning interval of each indicator is combined to determine the warning situation of each indicator.

II. Economic Management of Enterprises in the Context of the Information Age

Economic management is one of the main contents of enterprise business activities. Economic management can prompt enterprises to standardize and carry out all aspects of daily work in an orderly manner, and have a favorable impact on the management and development of enterprises, so that enterprises can carry out effective management and control in response to the current state of market competition, so that enterprises can always be compatible with the current market competition environment, so as to achieve the purpose of sustainable management, and to lay the foundation for the enterprise to develop to a higher level of development and the scope of business development. In addition, from the point of view of the development of the enterprise itself, how to use the resources of the enterprise reasonably, so as to maximize the economic interests of the enterprise is the basic goal of the development of the enterprise.

A. Enterprise economic management and business management

1) Economic management of enterprises in the information age

Big data technology plays an important role in the innovation of enterprise economic management mode, which can help enterprises better understand the market and customer demand, improve the accuracy and efficiency of decision-making, and promote the innovation of enterprise economic management mode.

First of all, big data technology can help enterprises better understand the market and customer demand. By collecting and analyzing a large amount of data, enterprises can more accurately understand market trends, consumer behavior and competitors, thus providing strong support for product development, marketing and strategic decision-making.

Second, big data technology can improve the accuracy and efficiency of enterprise decision-making. Traditional decisionmaking is often based on experience and intuition, while big data technology can provide enterprises with a more scientific and accurate basis for decision-making through data mining and analysis. This helps reduce decision-making risks and improve decision-making efficiency and accuracy.

Finally, big data technology can promote the innovation of enterprise economic management mode. With the intensification of market competition, enterprises need to constantly explore new management models and means. Big data technology provides enterprises with new management ideas and methods, which can help enterprises achieve more refined management and improve management efficiency and competitiveness.

2) Big data-driven financial analysis and corporate decision-making

With the rapid development of information technology and the arrival of the big data era, big data has become an important resource for enterprise decision-making. In the financial field, big data-driven financial analysis, as an emerging analysis method, is gradually being widely adopted by enterprises. By utilizing massive and diversified data, combined with advanced analytical techniques and algorithms, big data-driven financial analysis is able to reveal deeper financial information, thus providing more accurate and comprehensive support for corporate decision-making.

B. Accurate classification of enterprise financial data based on clustering algorithm

1) Financial data processing

As one of the core applications of digital technology, big data analytics plays an important role in modern economic management. It involves processing and analyzing largescale data sets, which often contain massive, diverse and high-dimensional data that cannot be handled by traditional databases. Through the use of advanced data-processing techniques, big data analytics is able to reveal patterns, correlations and trends hidden in massive amounts of data, and provide valuable information and insights to enterprises and decision makers.

2) Financial Data Denoising and Dimensionality Reduction Processing

1) Data denoising

Based on the clustering algorithm for accurate classification of massive corporate financial data, the PCNN model is used for the denoising processing of corporate financial data, the PCNN model can be categorized as a nonlinear non-static neural network, and the components contain a number of neurons, and the expression of the PCNN model is as follows:

$$\begin{cases} G_{ij}[n] = W_g \sum_{kj} N_{ijk} Z_{kj}[n-1] + f^{-b} G_{ij}[n-1] + T_{ij} \\ M_{ij}[n] = W_m \sum_{ij} N_{ij} Z_{ij}[n-1] + f^{-b} G_{ij}[n-1] \\ V_{ij}[n] = (1 + \chi M_{ij}[n]) G_{ij}[n] \\ Z_{ij}[n] = \begin{cases} 1V_{ij}[n] > \vartheta_{ij}[n] \\ 0V_{ij}[n] \le \vartheta_{ij}[n] \\ \vartheta[n+1] = W_s Z_{ij}[n] + f^{-\beta} \vartheta_{ij}[n] \end{cases} \end{cases}$$
(1)

where $G_{ij}[n]$ denotes n infusions at the *i*nd and *j*rd neurons. $M_{ij}[n]$ represents the input link, and T_0 represents the external giving signal. $N_{ijk1}Z_{k1}$ represents the coefficient model between channels G and M. $V_{ij}[n]$ represents the state signal, ϑ_{ij} represents the threshold during dynamics, β represents the corresponding deceleration time. W represents the corresponding fluctuation coefficients, and $Z_{ij}[n]$ represents the neuronal output.

A continuous neuron consists of three parts, the receptive domain, the output pulse part, and the modulation domain. The receptive domain is responsible for receiving external information and feedback from the neuron and then outputting the information to the outside. After the control neuron fires the output, the pulse part is responsible for comparing the dynamic threshold with the signal embodying the internal state. The internal state signal is then derived by multiplying the modulation domain with the synaptic link strength. When noise reduction is performed on massive corporate financial data according to the characteristics of the PCNN neuron model, it is divided into the following steps:

• Step1: Reset the network data.

- Step2: Build the data matrix N using the normalized data and judge the elements present in the matrix to obtain a new matrix.
- Step3: Using the elements present in the new matrix Y, determine the noise points present in the massive hospital financial data and filter the financial data.
- Step4: Calculate the mean square error of the data points after the filtering process and compare the calculated results with the initial mean square error.
- Step5: Output the noise reduction results and inverse normalization to complete the denoising of massive enterprise financial data.

2) Data dimensionality reduction processing

With the premise of data differentiation and dimensionality reduction, the automatic adaptation domain selection method is introduced to reduce the dimensionality of the financial data after the denoising process has been completed. This algorithm predicts the neighborhood dimension and local direction of financial data features, aggregates sample points with similar features, and completes data dimensionality reduction, the detailed steps are as follows:

- 1) Denote the size of the neighborhood of the financial data by k. This value can be calculated using the adaptive neighborhood selection method.
- 2) Find all the nearest neighbors of the financial data sample points by the following formula, and the distance *e* that exists between the financial data sample points and the neighboring points can be obtained by the following formula:

$$e_{ij} = \left[\sum_{k=1}^{E} |y_{ik} - y_{jk}|\right]^{\frac{1}{q}},$$
 (2)

where q denotes the Euclidean distance and y denotes the high latitude space.

3) Set the local reconstruction weight matrix as w_{ij} , and combine the constraints to transform the massive hospital financial data dimensionality reduction problem into an optimization problem:

$$\min \phi(y) = \sum_{i=1}^{o} \left\| \sum_{j=1}^{k} w_{ij} \left(y_i - y_j \right) \right\|^2 = \sum_{i=1}^{O} \left(y_i \right)^U A_i y_i$$
(3)

4) Introduce multipliers to solve the following problems:

$$M(Y) = \mu\left(\sum_{i=1}^{k} y_i - 1\right) + \sum_{i=1}^{o} (x_i)^T A_i y_i, \quad (4)$$

where A is the local variance matrix, M is the introduced multiplier, and O is the number of operations.

5) The optimized high latitude space data is put into the low latitude space to complete the dimensionality reduction of the hospital financial data. Using the ANS algorithm for dimensionality reduction of massive hospital financial data not only ensures that the dimensionality reduced financial data can retain the internal characteristics of the original data, but also obtains more specific 2D embedding results.

Compared with the autoencoders noise treatment of the PCNN model, the comprehensive evaluation index, the MSE, PSNR and NIQE has achieved a good result, and further verified the effectiveness and robustness of the algorithm, and the general reason for the noise.

- 3) Financial data processing based on clustering algorithms
 - 1) Objective function

Assume *d*-dimensional sample dataset:

$$X = \{ x_i \mid x_i \in \mathbb{R}^d , i = 1, \cdots, N \}.$$
 (5)

It is a dataset to be classified and its n clusters are denoted by F_1, F_2, \dots, F_n and their center data points are c_1, c_2, \dots, c_n , respectively, and:

$$c_i = \frac{1}{k_i} \sum_{x \in F_i} x \left(1 \le i \le n \right), \tag{6}$$

where k_i is the number of data points in cluster F_i and x denotes a certain data point in cluster F_i . In general, let Ob denotes the objective function of the clustering algorithm, whose mathematical expression is shown in (7):

$$Ob = \sum_{i=1}^{n} \sum_{j=1}^{k} d_{ij} (c_i, x_j), \qquad (7)$$

where $d_{ij}(c_i, x_j)$ denotes the Euclidean distance between a data point x_j in the data cluster F_i to the data center point c_i , i.e., it measures the sum of Euclidean distances between each data point to the data center point. At this point, the smaller the value of the objective function Ob is, the more compact the distribution of the classification is. When the objective function Obreaches the minimum value, its corresponding clustering method is optimal.

2) Specific steps

Using the basic principle of K-means clustering algorithm and the objective function, the specific steps of the clustering algorithm used in the enterprise financial system are formulated, and the K-means algorithm needs to perform multiple rounds of iteration. The specific iteration process of the K-means algorithm is shown in Figure 1, and its specific content is as follows:

1) The *d*-dimensional sample data set is:

$$X = \{ x_i | x_i \in \mathbb{R}^d, i = 1, \cdots, N \}.$$
 (8)

Select *n* initial data center points from the *d*-dimensional sample dataset, denoted by c_1, c_2, \dots, c_n respectively.

2) Divide the data set using c_1, c_2, \dots, c_n as the center point, which follows the principle, such that $i, l = 1, 2, \dots, n, j = 1, 2, \dots, k_i$ and $l \neq i$.



Figure 1: The specific execution process of the k-means clustering algorithm

If

$$d_{ij}\left(c_{i}, x_{j}\right) < d_{ij}\left(c_{i}, x_{j}\right),\tag{9}$$

then data point x_j is assigned to cluster F_i .

$$c_i = \frac{1}{k_i} \sum_{x \in F_i} x. \tag{10}$$

3) Use (10) to calculate the data center point $c_1^s, c_2^s, \cdots, c_n^s$ for round *s* of cluster F_1, F_2, \cdots, F_n .

$$\forall i \in \{1, 2, \cdots, n\}, \tag{11}$$

$$c_i^s = c_i^{s+1}.$$
 (12)

- If Eq. (11) and Eq. (12) hold, or if the number of iteration rounds of the algorithm exceeds the maximum number of iterations allowed, end the execution of the algorithm. Output the data center point result c₁^{s+1}, c₂^{s+1}, ..., c_n^{s+1} to form the final cluster. Otherwise, make the data center point result of round s + 1 as a new cluster and jump to b to continue the execution.
- 5) Output the clustering result of the dataset.

C. Early warning of corporate financial crisis based on particle swarm optimization algorithm

1) Financial risk projection

Big data analytics plays an important role in the field of risk management, as financial institutions can analyze big data to identify potential credit risks, monitor market volatility, predict trading risks and take appropriate measures to reduce risks. In the insurance field, big data analytics can also be used for accurate pricing and claims prediction to improve the efficiency of insurance business. And, big data analytics can help companies optimize supply chain management. By analyzing data from all parts of the supply chain, companies can monitor inventory levels, forecast demand, and optimize production plans in real time to ensure efficient and on-time production and distribution.

2) PSO-SVM early warning model for financial crisis

- 1) Particle Swarm Optimization Algorithm (PSO)
 - PSO is an optimization tool based on superposition, where the system is initialized as a set of random particles (random solutions) and searches for the optimal value through superposition. In each superposition, the particles update themselves by tracking two "extreme values". The first one is the optimal solution found by the particle itself, which is called the Individual Extreme Value p_{id} . The other extreme value is the optimal solution found by the whole population so far, which is the Global Extreme Value p_{gd} . When these two optimal values are found, the particles update their velocities and new positions according to the following formula. The formula is as follows:

$$V_{id} = w \times V_{id} + c_1 \times rand() \times (p_{id} - x_{id}) + c_2$$
$$\times Rand() \times (p_{sd} - x_{id}).$$
(13)

$$x_{id} = x_{id} + V_{id}, \tag{14}$$

where V_{id} is the velocity of the particle, x_{id} is the current position of the particle, p_{kd} is the individual extreme value. p_{gd} is the global extreme value, Rand() is a random number between $(0, 1), c_1, c_2$ is the learning factor, usually $c_1 = c_2 = 2c_1$. w is the inertia weight, which is used to control the effect of the velocity generated by the previous iteration on the velocity of the current iteration, usually $w \in [0, 1]$.

The velocity of the particles in each dimension is limited to a maximum velocity of $V_{\rm max}$. If the updated velocity of a dimension exceeds the user-set $V_{\rm max}$, then the velocity of that dimension is limited to $V_{\rm max}$.

PSO also randomly initializes the population, uses the adaptation value to evaluate the system, and also both perform a certain random search based on the adaptation value. However, PSO has no genetic operation, and the whole search and update process is a process of following the current optimal solution. Compared with GA, in most cases, all the particles in PSO may converge to the optimal solution faster. It can be seen that PSO has advantages in the optimization algorithm that GA can not be compared with, with simple operation and faster speed of obtaining the optimal solution.

2) PSO-SVM financial crisis early warning model

One of the biggest problems of SVM is how to choose the appropriate values of kernel function parameters, so that the model has the best classification and prediction performance. In general, the choice of feature set and kernel function parameters have an impact on the prediction accuracy of the model. Therefore, in order to obtain the best prediction results, the parameters of feature set and kernel function should be optimized at the same time. The selection of feature set and kernel function parameters are optimized simultaneously by PSO optimization algorithm to obtain the near-optimal feature subset and kernel function parameters, so as to improve the prediction performance of SVM-based model.

The SVM classification results are used as the adaptation value of the particles, and the adaptation value function is shown in (15). The sample data of the PSO-SVM model is divided into two parts, one part of which is used to train the model and the other part is used to test the model, to obtain the adaptation value of the particles, and the position of the particles (the feature set and the kernel function parameter) is continuously updated (optimized) by the adaptation value, and the process repeats itself until it meets the termination condition (In this paper, the maximum number of iterations is used as the termination condition of the algorithm), and finally a satisfactory solution is obtained. That is:

$$Fitness = \frac{\sum_{i=1}^{V_{mit}} M_i}{V_{size}},$$
(15)

where V_{size} is the size of the test set and M_i is the match between the predicted and actual results. When the predicted and actual results are the same, M_i is 1 and vice versa is 0. It can be said that Fitness is the average classification accuracy of the SVM model.

- The PSO-SVM workflow is shown in Figure 2, and the specific work steps are:
- Step 1: Define the position of particle $\{V_1, V_2, V_3\}$. V_1 represents the parameters of kernel function C, V_2 represents the parameters of kernel function δ^2 , V_3 represents the feature set.
- Step 2: Define the size of the population (n).
- Step 3: Generate *n* particles randomly.
- Step 4: If the loop stop condition (after traversing all the particles) is not satisfied, execute Step 5-9.
- Step 5: Decode the positions of the particles to get the 2 parameters and feature subset of the kernel function.
- Step 6: Apply the parameters and feature subsets to the SVM model and calculate the prediction results.
- Step 7: Compare the prediction result with the actual result to get M_i . Calculate the adaptation value of the particle through the adaptation value function.
- Step 8: Calculate the adaptation value of the population. Memorize the position information of individual extreme value and global extreme value.
- Step 9: Update the particle position.
- Step 10: Repeat Step 4 to Step 9 until the termination condition (maximum number of iterations) is satisfied.
- Step 11: Output the particle positions of the optimal adaptation values, i.e., the near-optimal kernel function



Figure 2: Process of PSO-SVM Model

parameters and feature subsets. At the same time, get the near-optimal prediction results.

III. Analysis of Empirical Results

A. Sample Selection and Description

Before establishing the financial risk early warning system, on the one hand, it is necessary to understand the company profile of Company Y, including the business scope of the enterprise, the industry classification, the company's business strategy and other basic information, in order to have a general grasp of the situation of the enterprise. On the other hand, it is necessary to understand the financial situation of Company Y. This paper starts from the financial statements of Company Y and the identification of financial risks to carry out financial analysis of Company Y.

1) Assets and liabilities analysis

By analyzing the financial statements of Company Y for the past six years, we can see the trend of changes in assets and liabilities, operating conditions, and cash flow and other financial conditions and further analyze the reasons behind them, so as to gain an in-depth understanding of Company Y's financial status.

The main data of the assets and liabilities of Company Y in the past six years are shown in Table 1, in the composition of assets, the current assets show a fluctuating trend, among which the change of monetary funds is the most obvious, with monetary funds of 631.52 million yuan in 2018 and 286.54 million yuan in 2019, a decrease of 344.98 million yuan. The sharp decline in monetary funds in 2019 was related to the speed of receivables recovery and the decline in product sales. The sharp decline in corporate liquidity can easily affect the short-term solvency. From 2016 to 2020, the owner's equity increased year by year, with the largest increase in 2020, reaching 256351 million yuan. It is due to the implementation of the non-public plan for the issuance of new shares during the year, and the issuance of new shares. The funds raised this time will be used to supplement the company's cash flow, so that the company has stronger financial strength to continue to focus on the research and development of the intelligent equipment industry. At the same time, there are also enough funds to support the company to undertake hundreds of millions of yuan of large orders.

2) Profit analysis

The main profit data of Company Y in the past 6 years are shown in Table 2, except for R&D expenses, management expenses and financial expenses from 2016 to 2020, the rest of the items showed a fluctuating trend, and all reached a peak in 2018. The total operating income increased significantly in 2017 and 2018, with an increase of 783.44 million yuan and 161112 yuan compared with 2016. Total operating costs also reached their highest value of 225136 million yuan in 2018, mainly due to the impact of selling expenses and business taxes and additional items.

B. Financial Crisis Analysis Based on PSO-SVM Early Warning Models

1) Selection of financial indicators

In the research of this paper, we will measure and evaluate the difference and generalization between the model established in this paper and the traditional model through several aspects, so in this paper, we will measure the performance of the model from different perspectives through multiple sets of experiments. The traditional Logit and Probit models require strict assumptions when running, and the data required for the model to run must meet the normal distribution, so this paper will use the above screened indicators as sample data. The financial indicators of the first screening include eight dimensions: profitability, operational capacity, solvency, cash flow, equity structure, corporate governance, audit, and enterprise size.

Since the classification of support vector machine does not require any assumptions, and the restrictions on the requirements of sample data are more relaxed than those of traditional models, the more relaxed second screening will be used as the sample data of the PSO-SVM model established in this paper.

In this research, the importance level of indicator features is calculated and analyzed specifically using the replacement importance as a tool. The result obtained is the feature importance level, which can reflect the risk of data bias and the risk of model flaws.

There are a total of 15 financial indicators, including financial leverage, capital intensity, cash flow debt ratio, operating leverage, accounts receivable turnover, inventory turnover, cash and cash equivalents turnover, operating profit growth rate, consolidated leverage, gross operating margin, cash ratio, return on investment, capital accumulation ratio, gearing ratio, and current ratio.

2) Identification of indicator data

In this paper, the random sampling method will be used in the selection of sample data to determine the training samples and

Project	2016	2017	2018	2019	2020	2021
Monetary money	63251	68541	63152	28654	39164	22256
Accounts receivable	936	23641	36158	56259	43365	38054
Inventory	72115	95225	103556	123608	117024	103425
Total flow assets	189552	245621	246864	249165	235198	233051
Fixed assets	42518	400123	12563	10298	9869	156367
Construction project	15	506	296	1984	13226	17425
Intangible assets	2539	7458	8356	12362	12477	16239
Goodwill	-	58076	95221	95263	103251	78929
Total non-current assets	52136	123621	205694	225378	240569	245869
Total assets	223965	369212	456117	456935	503264	489251
Total current liabilities	65983	153691	235681	213221	198620	254606
Total non-current liabilities	3002	32654	38965	52123	52361	40212
Total liability	68932	189635	269554	245312	223511	289654
Total ownership	159225	169364	182112	189364	256351	196548

Table 1: Y company's total assets liabilities (RMB 10,000 yuan) for nearly six years

Project	2016	2017	2018	2019	2020	2021
Total revenue	75842	154186	236954	178596	165258	173422
Business assembly	123526	156240	225136	175425	170216	189002
R&d cost	-	3521	4528	8975	8963	8754
Sales cost	2135	7896	18966	142354	11528	15328
Management fee	13254	145998	13425	141856	110241	150036
Financial cost	-896	1253	2508	4251	7265	6539
Operating profit	-49563	147271	201534	610	-48525	-66019
Gross profit	-52135	15228	201112	5693	889	-65932
Net profit	-51442	12855	129365	4835	935	-61025

Table 2: Y company's total assets liabilities (RMB 10,000 yuan) for nearly six years

test samples, and for each warning result, the warning samples used are different. In order to fully reflect the performance and accuracy of the samples, this paper will use the method of multiple experimental comparisons to measure the established model. In terms of the use of sample data, this paper will use the original indicator data, i.e., the full indicator system data, the first screening data, the second screening data, respectively, in order to verify the generality of this model. In addition, the number of training samples in this paper is 100 listed companies and the test sample data is 50 listed companies.

In this paper, 20 experiments are used to evaluate the adaptability of the PSO-SVM model established in this paper to various types of data, respectively, to measure the performance of the model.

The test results of PSO-SVM model on indicator data are shown in Figure 3, which analyzes the test results of PSO-SVM model on the original indicator data, the first screening indicator data, and the second screening indicator data, and the mean values of the accuracy of the three test results are 0.892, 0.912, and 0.892, respectively, and the precision is in the interval of [?], [?]. The standard deviations are 0.036, 0.0235, and 0.0419, respectively, through which it can be seen that the neatness of the prediction results produced by the model is also getting better and better with the continuous optimization of the indicator system.

C. Enterprise financial early warning model applications



Figure 3: Test results of the PSO-SVM model for index data

1) Early warning intervals for indicators

The PSO-SVM model was used for variable calculation, and also combined with the use of partial correlation function to measure the role of the value of a variable on the probability of the occurrence of a category is high or low.

The early warning intervals of each financial indicator are shown in Table 3, and the weights and early warning intervals of each financial indicator are calculated, taking the financial leverage indicator as an example, its weight and early warning intervals are 0.0412 ± 0.0045 and greater than 1.75, respectively, and the early warning intervals of the balance sheet ratio are less than 0.52 or greater than 0.76.

The order of the indicators in the table is not set arbitrarily, but strictly in accordance with the importance of the characteristics to be arranged. The table can show the enterprise's profitability, development potential and operational level of early

Index	Weighting	Warning interval
Financial leverage	0.0412 ± 0.0045	>1.75
Capital intensity	0.0235 ± 0.0041	>6.12
Cash flow debt ratio	0.0218±0.0019	<1.33
Operating lever	0.0099 ± 0.0018	>1.75
Receivable turnover	0.0097 ± 0.0004	<1.87
Inventory turnover	0.0072 ± 0.0010	< 0.63
Cash and cash equivalents	0.0038 ± 0.0021	<1.32
Rate of operating profit	0.0042 ± 0.0019	<-0.99
Integrated lever	0.0049 ± 0.0011	>1.51
Operating rate	0.0044 ± 0.0033	< 0.96
Cash ratio	0.0036 ± 0.0022	< 0.51
Investment yield	0.0025 ± 0.0025	<-0.005
Capital accumulation rate	0.0039 ± 0.0021	< 0.007
Asset ratio	0.0041 ± 0.0028	<0.52 or >0.76
Mobility ratio	0.0032 ± 0.0019	< 0.62

Table 3: Warning intervals of each financial indicator

warning indicators, the values obtained are generally low, in line with the actual situation, indicating that the enterprise's profitability, development potential and operational level have more room for improvement. The provision of financial early warning intervals can make the relevant model easier to be understood by the public, and can also give a certain reference to the assessment of the financial development of the enterprise.

2) Indicator early warning judgment

If a listed company's net profit is negative for two consecutive years, it will trigger the delisting warning, i.e., it will be ST. So in order to judge whether the company will be ST in the Tth year or not, this paper collects the data of important indexes of listed companies in the Tth-3rd year.

Since the financial index situation of Company Y in the T-3rd year is the direct influence factor of its financial data in the Tth year, this paper chooses the relevant data of the company in 2020 as the focus of analysis, from which it determines the operation status of Company W in 2023 and the financial risk it faces.

In this paper, the financial data of company Y in 2020 is obtained from the database, and the PSO-SVM model is trained according to the method introduced in the previous section, if the result is 0, it means that the company is not ST. If the result is 1, it means that the company is ST.

In this paper, the annual report data of company Y in 2020 is collected and put into the PSO-SVM model for prediction, and the result is 1, which indicates that company Y is a ST company in 2023.

The early warning interval of financial indicators of Company Y is shown in Table 4, which demonstrates the value of each indicator of Company Y in 2020 and makes a judgment on whether each indicator is in the early warning interval or not.

Comparing the indicator values of Company Y with the early warning interval, it can be seen that nine indicator values of high importance of Company Y in 2020 have entered the early warning interval, and the comprehensive leverage index is 12.793681, which has seriously exceeded the normal range,

	Indexing	Is it in the early warning interval
Financial leverage	4.608125	Yes
Capital intensity	13.001205	Yes
Cash flow debt ratio	-0.018693	Yes
Operating lever	1.661011	NO
Receivable turnover	1.542051	Yes
Inventory turnover	0.663650	NO
Cash and cash equivalents	1.393612	NO
Rate of operating profit	-0.990069	NO
Integrated lever	12.793681	Yes
Operating rate	0.953699	Yes
Cash ratio	0.501233	Yes
Investment yield	-0.006358	NO
Capital accumulation rate	0.005211	Yes
Asset ratio	0.519325	Yes
Mobility ratio	0.689959	NO

Table 4: The financial index warning interval of y company

which deserves to draw the full attention of Company Y's managers.

IV. Case analysis

In this paper, three kinds of data from the squirrel have been analyzed in recent years, and the results of the annual comprehensive warning are that the three squirrel cases are in the case of the police in 2017, and the company's financial situation has a certain problem. Although the financing size increased in 2018, the money was relatively sufficient, the police became light police, but it fell to the police in 2019, and for two years, it showed that the company had improved its financial situation by external forces, but the fundamental problem was not solved. In particular, the five years of early warning scores can be seen that the score of only 0.55 in 2019 is low, compared with the previous classification of 0.5-0.7, which is relatively close to the alert, and the financial risk of the three drivers in 2019 is serious. After two years of police and police, three of them are turning to light police in 2021, but although there is a good tendency to be good, the company is still unable to relax its vigilance because of the latent period of financial risk in 1-2 years.

V. Conclusion

The purpose of this paper is to reflect that economic management analysis combined with information technology plays an important role in enterprise operation and management. The proposed enterprise financial data processing technology based on clustering algorithm, and then introduce the particle swarm optimization algorithm for enterprise financial crisis early warning, for the development of enterprise management to put forward important decisions.

Combined with the clustering processing of enterprise financial data, the enterprise's assets and liabilities analysis and profit data in the past six years are obtained. Using PSO-SVM financial crisis early warning model for enterprise risk prediction, we get a total of nine indicators of the enterprise appeared early warning situation, including financial leverage, capital intensity, cash flow debt ratio, accounts receivable turnover, indicators appeared early warning, comprehensive leverage, gross operating margin, cash ratio, capital accumulation rate, asset-liability ratio, which the comprehensive leverage index is 12.793681, which has been seriously exceeded the normal range, which deserves the full attention of Company Y's managers. Company managers should pay special attention to these business indicators that appear as early warning situations when formulating enterprise management programs.

The use of information technology to carry out scientific and rational research on the development of economic management activities ensures that the enterprise has sufficient financial and material resources in each line of business, which in turn enhances the management level of the enterprise. This paper analyzes the problems existing in the current new situation, the enterprise economic management work, and with the actual development of the enterprise itself, for these problems, put forward the effective comprehensive optimization countermeasures, which is very instructive to improve the level of enterprise operation.

Because of the limitation of the author's ability, this paper is a problem of the financial risk warning system, which is the financial index, the lack of non-financial indicators, and the research method of the selection of the paper is quantified, and the blind selection may reduce the scientific nature of the early warning system. However, non-financial indicators will also bring financial risks to enterprises, so we hope to increase the discussion of non-financial indicators in future studies. Second, in the selection of the industry reference standard value, because of the limitation of the document, the food retailing industry is selected, and the size, rules and regulations of the enterprise, the management of the management, will also bring a certain difference, so the further study will need to explore the more rigorous and scientific reference values.

References

- Al-Kharusi, H., Miskon, S., & Bahari, M. (2021). Enterprise architects and stakeholders alignment framework in enterprise architecture development. *Information Systems and e-Business Management*, 19(1), 137-181.
- [2] Cowan, K., Palo, T., Chapple, D., & Zhang, Y. (2023). Market amplification or transformation? The role of industry analysts in spreading WOM in B2B. *Journal of Business & Industrial Marketing*, 38(8), 1623-1638.
- [3] Jiaping, X., Luhao, L., Ling, L., & Weisi, Z. (2017). Coordination for value networks of agricultural social enterprises: an empirical analysis from the perspective of social embeddedness. *Journal of Finance and Economics*, 43(10), 83-96.
- [4] Guo, A., Wei, H., Zhong, F., Liu, S., & Huang, C. (2020). Enterprise sustainability: Economic policy uncertainty, enterprise investment, and profitability. *Sustainability*, 12(9), 3735.
- [5] Gibbons, J., & Hazy, J. K. (2017). Leading a large-scale distributed social Enterprise: How the leadership culture at goodwill industries creates and distributes value in communities. *Nonprofit Management and Leadership*, 27(3), 299-316.
- [6] Li, Q., Shan, H., Tang, Y., & Yao, V. (2024). Corporate climate risk: Measurements and responses. *The Review of Financial Studies*, 37(6), 1778-1830.
- [7] McCaffrey, M. (2018). Extending the economic foundations of entrepreneurship research. *European Management Review*, 15(2), 191-199.
- [8] Alcalde-Heras, H., Iturrioz-Landart, C., & Aragon-Amonarriz, C. (2019). SME ambidexterity during economic recessions: the role of managerial external capabilities. *Management Decision*, 57(1), 21-40.
- [9] Leitner, K. H., Poti, B. M., Wintjes, R. J., & Youtie, J. (2020). How companies respond to growing research costs: cost control or value creation?. *International Journal of Technology Management*, 82(1), 1-25.

- [10] Li, C. S. J., Lee, P. Y., & Liou, J. J. (2018). Exploring the staff localization of Taiwanese MNC subsidiaries in China: Effects of size, operation time, location, and local-market focus. *Journal of Business Research*, 88, 20-27.
- [11] Oguji, N., Owusu, R. A., & Larimo, J. (2019). Determinants of equity changes in partial acquisitions of Finnish multinationals in foreign markets. *Baltic Journal of Management*, 14(2), 268-290.
- [12] Haak-Saheem, W., & Festing, M. (2020). Human resource management–a national business system perspective. *The International Journal of Human Resource Management*, 31(14), 1863-1890.
- [13] Marathe, G. M., Dutta, T., & Kundu, S. (2020). Is management education preparing future leaders for sustainable business? Opening minds but not hearts. *International Journal of Sustainability in Higher Education*, 21(2), 372-392.
- [14] McCaffrey, M. (2018). Extending the economic foundations of entrepreneurship research. *European Management Review*, 15(2), 191-199.
- [15] Bu, X., Cherian, J., Han, H., Comite, U., Hernández-Perlines, F., & Ariza-Montes, A. (2022). Proposing employee level CSR as an enabler for economic performance: The role of work engagement and quality of worklife. *Sustainability*, 14(3), 1354.
- [16] Zhong, T., Zuo, Y., Sun, F., & Lee, J. Y. (2020). Customer concentration, economic policy uncertainty and enterprise sustainable innovation. *Sustainability*, 12(4), 1392.
- [17] Tu, J. C., Chan, H. C., & Chen, C. H. (2020). Establishing circular model and management benefits of enterprise from the circular economy standpoint: A case study of Chyhjiun Jewelry in Taiwan. *Sustainability*, *12*(10), 4146.
- [18] Klimek, D., & Jędrych, E. (2020). A model for the sustainable management of enterprise capital. *Sustainability*, 13(1), 183.

...