Listed Company Financial Crisis Early Warning in the Electronic Information Industry Based on QBPSO-SVM

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ABSTRACT. The purpose of this research paper is to construct a financial crisis early warning model for Chinese listed companies in the electronic information industry, validate the model based on the collected data, and give corresponding suggestions based on the experimental results.

The main research objectives of this paper are 1) to identify 13 financial indicators and crisis factors; 2) to establish an early warning model and indicator system; and 3) to validate and improve the early warning model. The research method of this paper is the quantitative study of 13 financial indicators combined with the algorithm of Quantum Behavioral Particle Swarm Optimization Support Vector Machine to verify the applicability of the early warning model of financial crisis for listed companies in the electronic information industry.

The research content is through the China Securities Regulatory Commission designated information disclosure website of listed companies CNINFO (www.cninfo.com.cn) to select the economy of the top 155 A-share listed companies in the electronic information industry as the research sample overall, according to the principle of financial indicators to determine the final selection of the sample group of 76 A-share listed companies in the electronic information industry. Considering the variability of market data to determine the screening statement data for 2017-2021. The designated samples must comply with the domestic accounting standards; no bankruptcy, no write-off of normal operation of the company, from the electronic information industry, with the shape of the asset size, the same time period. Experimental validation of quantum behavior particle swarm optimization support vector machine financial crisis early warning model for electronic information industry is carried out through matlab modeling software. The specific algorithm is to optimize the SVM by QBPSO algorithm to get the optimal parameters, import the financial index data from 2017 to 2021 into the model test, and the final result reaches 94.54%.

The results of the research are as follows: this thesis uses the quantum behavior particle swarm optimization algorithm on the utility of support vector machine in the financial crisis early warning of listed companies in the electronic information industry.

Keywords: PSO, SVM, Quantum behavior strategy, Inertial weight, Financial crisis.

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1 Introduction

As China's stock market develops and regulation of listed companies increases, financial crisis early warning models using financial statement data have become vital (Chen Zhibin, Tan Ruijua,2006)[1]. However, most models employ unified systems rather than accounting for industry differences. This study develops early warning models specific to the electronic information industry using 13 financial indicators, and compares monistic and multiple decision models. Scholars have pioneered alternative mode linputs like(Altman,1968)[2]Z-score model, particle swarm optimization (PSO) and support vector machines (SVM). However, limitations exist with current PSO and SVM models. In order to solve these limitations, the causes of corporate financial crisis, the selection of indicators and the early warning process are analyzed through research, and based on which financial and non-financial indicators are selected to form the early warning indicators of financial crisis of science and innovation enterprises. (Zhan Chen, 2023)[3]Based on this research, this paper proposes a quantum behavioral particle swarm QBPSO-SVM model for the electronic information industry, which makes full use of the advantages of these two algorithms and combines the indicators to establish a financial crisis early warning model. The proposed model can provide crisis early warning for the status and financial indicators of the electronic information industry, which is of great significance for listed companies in the electronic information industry.

2 Objective

1.Identify 13 financial indicators and crisis factors.

2.Establishing QBPSO-SVM early warning model.

3.Validate the validity and feasibility of the financial crisis early warning model and indicator system based on QBPSO-SVM.

3 Scope of Research

Scope of Content.

This research is a study of financial crisis early warning for listed companies in the electronics industry based on QBPSO-SVM, which contains the following variables:

Independent variables in this study comprise 13 financial indicators, each derived from the standard formulas outlined in "Financial Management" (8th ed.) by Wang, J., Wang, H., and Liu, J. (2018)[4].

1.Current ratio (X1): Current ratio = Total current assets / Total current liabilities * 100%.

2.Quick ratio (X2): Quick ratio = Quick assets / Current liabilities * 100%. Where quick assets = Current assets – Inventory.

3.Cash ratio (X3): Cash ratio = (Cash + Trading financial assets) / Current liabilities * 100%.

4.Debt-to-asset ratio (X4): Debt-to-asset ratio = Total liabilities / Total assets * 100%.

5.Return on assets (X5): Return on assets = Net profit after tax / Total assets * 100%.

6.Return on equity (X6): Return on equity = Net income / Shareholders' equity * 100%.

7.Inventory turnover rate (X7): Inventory turnover rate = Cost of goods sold / Average inventory * 100%. Where.

1). Cost of goods sold = Unit cost per sale * Number of units sold.

2) Average inventory = (Inventory at beginning + Inventory at end) / 2.

Total asset turnover (X8): Total asset turnover = Operating revenue / Average total assets * 100%. Where average total assets = (Total assets at beginning + Total assets at end) / 2.

8.Growth rate of total assets (X9): Growth rate of total assets = Increase in total assets this year / Total assets at beginning of year * 100%. Where increase in total assets this year = Total assets at year end - Total assets at beginning of year.

9.Growth rate of net profit (X10): Growth rate of net profit = (Net profit this year - Net profit last year) / Net profit last year * 100%.

10.Growth rate of operating revenue (X11): Growth rate of operating revenue = (Increase in operating revenue / Total operating revenue last year) * 100%.

11.Financial leverage ratio (X12): Financial leverage ratio = Growth rate in EPS / Growth rate in EBIT.

12.Cash flow ratio (X13): Cash flow ratio = Net cash flow from operations / EBIT = Net cash flow from operations / ((Operating revenue - Cost of goods sold - Operating expenses) * (1 - Actual income tax rate)).

Dependent Variable:

The financial crisis early warning model was established through the function obtained by QBPSO-SVM.

Scope of Population.

A sample of 76 A-share listed companies from the electronics and information technology industry were selected as the research sample for this study using Krejcie and Morgan's table (1970). The sample was screened from the CNINFO database (www.cninfo.com.cn).

Scope of Area.

The scope of area is limited to A-share listed companies in China's electronics and information technology sector.

Scope of Time.

June 2022 to October 2023.

4 Research Methodology

This study develops a financial crisis early warning model for 76 randomly selected A-share listed companies in China's electronic information sector from 2017-2021. A quantitative analysis compares a QBPSO-SVM model against benchmarks (Experiment 1) and state-of-the-art alternatives (Experiment 2). 13 financial indicators across solvency, profitability, operations, growth, risk and cash flow are selected based on scholarly research. The 13 financial indicators used as inputs are summarized below (Table 1):

Table 1. Financial early warning indicator system for listed electronic information companies

Level 1 Indicators	Secondary Indicators	Three-level Indicators
Financial early warning indicator system for listed companies with electronic information	Solvency	Current ratio (X1)
		Quick ratio(X2)
		Cash ratios(X3)
		Gearing ratio(X4)
	Profitability	Return on assets(X5)
		Return on equity(X6)
	Operational capabilities	Inventory turnover(X7)
		Total asset turnover(X8)
	Develop capacity	Growth rate of total assets(X9)
		Net profit growth rate(X10)
		Revenue growth rate(X11)
	crisis level	Financial leverage(X12)
	Cash flow analysis	Net cash content of operating profit(X13)

Data comes from audited statements on CNINFO. Stringent criteria ensured representative healthy and distressed firms.

The QBPSO algorithm is first tested on benchmarks for optimization accuracy, convergence speed and stability before integration with the SVM classifier (RBF kernel). QBPSO optimizes the SVM parameters C and gamma in a 2D search space. The model is implemented in MATLAB using SVM libraries. Separate training and testing sets are utilized.

The key performance metrics are computational accuracy and convergence speed. The model aims to effectively predict financial crises in this sector based on the latest data and tailored optimization.

5 Model Development

The QBPSO-SVM model was implemented in MATLAB using SVM libraries. The model workflow was as follows:

1. Import and preprocess financial dataset to divide into training and test sets.
2. Initialize QBPSO population randomly and calculate fitness based on Equation 3:

$$\text{Fitness} = f(C, \gamma)$$

Where C and γ are the SVM parameters optimized by QBPSO.

3. Train model on QBPSO-optimized parameters until convergence criteria met.
4. Input test set into trained model to output financial crisis predictions.

Training involved inputting the preprocessed data into the SVM model optimized by QBPSO to derive the parameters C and γ. Testing involved importing the trained model on the holdout test set to output predictions.

The key performance metrics tracked were computational accuracy and convergence speed during QBPSO optimization. The overall workflow is depicted in Figure 1. This implementation in MATLAB enabled effective development and evaluation of the QBPSO-SVM model for financial crisis prediction.

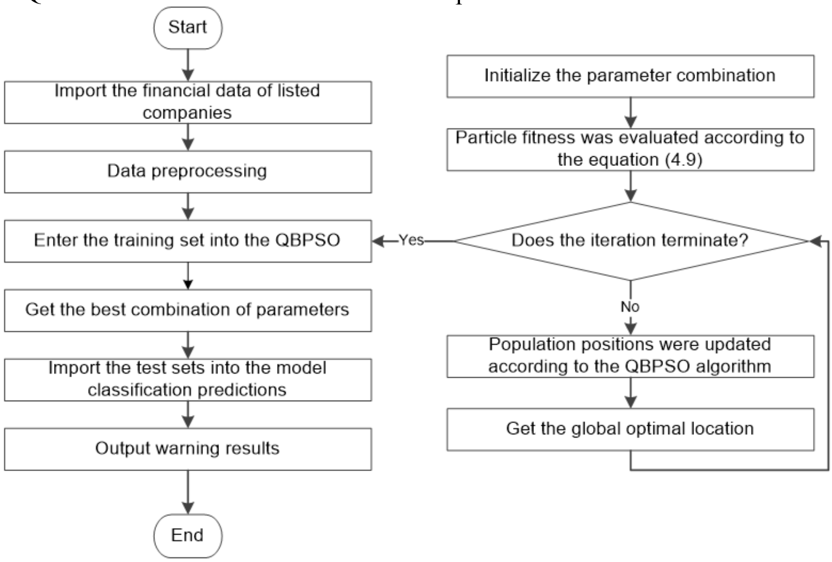

Fig. 1. QBPSO-SVM Algorithm Flow Chart

6 Result

Descriptive analysis tested the QBPSO algorithm against GWO, MPSO and IAGA on 23 benchmark functions in 30 and 50 dimensions. QBPSO showed superior optimization and stability on most unimodal and complex multimodal functions. Convergence curves demonstrated QBPSO continued optimizing after the other algorithms plateaued.

Inferential analysis evaluated a QBPSO-SVM model predicting financial crises against CS-SVM, PSO-SVM and DE-SVM models. The QBPSO-SVM model achieved highest accuracy of 96.07% (mean 94.54%), with zero standard deviation, indicating excellent stability. CS-SVM accuracy was 93.12%, PSO-SVM 92.48%, and DE-SVM 92.18%.

Results verify the optimization capability of QBPSO and feasibility of a QBPSO-SVM model for financial crisis forecasting, with high, stable predictive accuracy on par or superior to state-of-the-art alternatives.

7 Conclusion and Discussion

7.1 Conclusion

The selection of a 13-financial indicator system for early financial crisis warning in the electronic information industry's listed companies(Gao Ming, Zhang Tianwei, 2020)[5], based on financial data from 2017 to 2021, is validated through comprehensive analysis across multiple facets of corporate performance. These indicators align with the findings proposed by Chen in 2022. The Quantum Behavioral Particle Swarm Optimized Support Vector Machine (QBPSO-SVM) model established in this study is consistent with the theory of scholars (Xinxin Xu, 2021) [6] proved that the support vector machine can be used for early warning research, and this paper optimizes the SVM parameters through the Quantum Behavioral Particle Swarm QBPSO algorithm. The experimental results show that the QBPSO-SVM model has a very high accuracy, emphasizing that the powerful generalization ability of SVM and the RBF kernel function are suitable for constructing an effective early warning system for financial crisis in the electronic information industry.

7.2 Discussion

The Differential Evolutionary Algorithm (DE) optimization study for the Support Vector Machine (SVM) financial crisis early warning model achieved an average accuracy of 92.18%, consistent with Storn and Price's 1995 proposal. However, continued algorithmic enhancements indicate its decreasing applicability to early financial crisis warning for electronic information industry's listed companies (Storn & Price, 1995)[7]

The Particle Swarm Optimization (PSO) for SVM financial risk early warning model yielded an average accuracy of 92.48%, aligning with Dr. Eberhart and Dr. Kennedy's 1995 study. Nonetheless, its performance remains suboptimal for financial crisis early warning in the electronic information industry (Eberhart & Kennedy, 1995)[8]

The Cost-Sensitive Learning (CS) optimized SVM financial risk early warning model achieved an average accuracy of 93.12%, in line with Wan Jianwu and Yang Ming's 2020 study. However, it does not emerge as the most effective experimental algorithm for financial crisis early warning in the electronic information industry (Wan Jianwu and Yang Ming, 2020)[9], LI Chenjie ,L(2019)[10]

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