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An Optimized Z-Score Financial Early-Warning Model for Foreign Trade Enterprises Using Stochastic Optimization Algorithm

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ABSTRACT

The paper proposed a model to assess and predict financial risks in Chinese foreign trade listed companies. Recognizing limitations in the traditional Altman Z-Score model such as low diagnostic accuracy the authors integrate the Stochastic Optimization Algorithm (SOA) to fine tune the model's coefficients. Using financial data from 20 listed firms and a five year case study of Jiangsu Sainty Co., Ltd. (2012–2016), they demonstrate that the SOA optimized Z-Score model significantly improves prediction accuracy, achieving a 96.33% recognition rate outperforming SVM and AdaBoost algorithms. The analysis reveals key financial indicators (e.g., retained earnings, EBIT, and asset turnover) critically influence risk levels. Based on findings, the authors recommend enterprises establish robust risk control systems, optimize capital structures, improve working capital management, and enhance profitability. The study underscores the value of combining classical financial models with modern optimization techniques for more reliable, adaptive financial risk assessment in dynamic market environments.

Keywords: Financial Risk, Z-Score Model, Stochastic Optimization Algorithm (SOA), Early-Warning System, Foreign Trade Enterprises, Financial Distress Prediction, Optimization, Empirical Analysis

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1. Introduction

The ability of businesses to achieve their long term development objectives is closely linked to their financial risk circumstances. Investigations into the financial risks faced by companies have increasingly emerged as a significant research focus in related disciplines [1]. In an ever more intricate market economic landscape, the financial risk for businesses is influenced not only by external macroeconomic factors but also by internal microfactors. Companies inevitably face financial risks due to the unpredictability stemming from internal and external factors. Regardless of the industry, substantial financial risk increases the likelihood of a bankruptcy crisis, which can severely hinder the stable, healthy growth of the national economy [2]. Against this backdrop, this paper provides a thorough evaluation of the financial risks inherent to the enterprise itself. It concludes with specific findings and offers practical recommendations for managing financial risk, which can positively impact the business's long term development goals [3]. Currently, research concerning the financial risks of foreign trade companies in China primarily focuses on categorizing these financial risks, control methods, and other related perspectives, yet there is a notable lack of targeted studies addressing the financial risks encountered by foreign trade enterprises in China [4]. Hence, this paper draws practical insights from advanced financial risk evaluation models from abroad, thoroughly examines the unique characteristics of businesses involved in foreign trade activities in China, and conducts an empirical analysis of the financial risks faced by these enterprises, contributing positively to the theoretical exploration of financial risks in Chinese enterprises [5].

2. Present Environment

The formal decision making model introduced by Fitzpatrick (1932) represents one of the earliest inquiries into enterprise financial risk warnings; he specifically selected 19 companies as his research subjects and categorized them into two groups based on a single level financial index: those that went bankrupt and those that did not [6]. Through empirical analysis, he found that two indicators net profit relative to shareholders' equity and shareholders' equity relative to liabilities exhibited significant discriminatory power [7]. Beaver (1966) chose 80 firms as his research samples to investigate and assess the predictive power of 40 variables that could indicate the characteristics of a company over a 1 to 8-year period leading to bankruptcy [8]. He was the original advocate of the Z-score model, which provided a comprehensive assessment of the financial risk businesses must confront [9]. The Z-score model focused on five essential financial metrics, selected five typical financial indicators, and computed the Z-score by assigning weights to the relevant indicators, thereby scientifically defining the company's financial risk status relative to a standard threshold [10]. Altman chose 40 bankrupt and 40 non bankrupt companies for a comparative analysis, utilizing the principle of minimizing the likelihood of misclassification to determine the weights of five key financial indicators, and developed multiple linear discriminant models [11]. Artin (1977) employed the logistic model to evaluate the risk of 6,000 companies selectively from 1980 to 1987. Upon comparison, it was determined that the predictive performance of the Logistic model is outstanding [12].

3. Methodology

3.1 Z-Score Model Construction

With the goal of scientific evaluation and early detection of risks associated with businesses and stocks that warrant investment, Professor Altman officially introduced the Z-Score financial early warning model, incorporating the actual economic conditions for the early warning analysis of publicly traded companies. He selected five financial indicators and multiplied them by different coefficients to construct the Z-Score financial early warning model, enabling practical risk analysis of publicly listed firms [13].

$$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X51 \qquad (1)$$

Z in formula (1) represents Z-Score, X_1, X_2, X_3, X_4, X_5 represent different types of financial indicators, X_1 = working capital / total assets; X_2 = retained earnings / total assets; X_3 = Net profit before interest and tax /

total assets; X_4 = shareholder equity/book value of total liabilities; X_5 = sales amount / total assets. According to formula (1), it can be concluded that Altman concludes that in the case of Z-Score ≥ 2.675, the financial state is sound, and Z-Score <2.675, the financial situation is not good, so the Z-Score model can be used to analyze the financial crisis of the listed company [14].

3.2 SQA Algorithm

The fundamental concept of the SOA algorithm is that it adeptly simulates the random search behavior of individuals and applies this intelligent search behavior to the problem of search optimization. Regarding the optimization calculation process, unexpected search actions of individuals can be understood as follows: during the search through continuous space, the more optimal solution is frequently located near the optimal solution, meaning that the optimal solution is likely to exist in the vicinity of the best solution [15]. Thus, if the search area is promising, searchers should narrow their search operations to smaller neighborhoods; conversely, if the area is unpromising, they should broaden their search to larger neighborhoods. It can be asserted that SOA effectively utilizes fuzzy logic and uncertainty reasoning based on natural language to model the aforementioned search principle and derive specific search steps. SOA harnesses social and cognitive learning to acquire essential social and cognitive experiences, and while effectively associating the self-organized clustering behavior characteristic of the intelligent community, it pursues actions that are advantageous to itself and establishes its search objectives.

The SOA algorithm includes the following steps: step1: t'!0; step 2: initialization can cause s initial positions in the domain of the feasible solution: $\{\vec{x}_i(t) | \vec{x}_i(t) = (x_{i1}, x_{i2}, ...x_{iM})\}$; step3: the objective function value of any position is evaluated and calculated; step4: it is needed to search mode, so as to calculate the search direction *dij(t)*and the step size *aij(t)* for any individual *i* in any dimension *j*, and define altruism as well as pre-action, self-interest orientation $\vec{d}_{i,ego}$, altruistic orientation $\vec{d}_{i,alt}$ and proactive orientation $\vec{d}_{i,pro}$ of any of the first *i* search individuals, and then the actual expression is:

$$\vec{d}_{i,ego}(t) = \vec{p}_{i,best} - x_i(t) \quad (2)$$

$$\vec{d}_{i,alt}(t) = \vec{g}_{i,best} - x_i(t) \quad (3)$$

$$\vec{d}_{i,pro}(t) = \vec{x}_i(t_1) - \vec{x}_i(t_2) \quad (4)$$

Considering the type (2), type (3), type (4), the direction of search is determined by random weighted geometric averaging of three directions. The search direction is shown in equation (5):

$$\vec{d}i_j(t) = sign(\omega\vec{d}_{ij,pro} + \varphi_1\vec{d}_{ij,ego} + \varphi_2\vec{d}_{ij,alt}) \quad (5)$$

In the formula (1) to (5), $\vec{x}_i(t_1)$, $\vec{x}_i(t_2)$ are the best positions in $\vec{x}_i(t-2)$, $\vec{x}_i(t-1)$, $\vec{x}_i(t)$ respectively; $\vec{g}_{i,best}$ is the collective historical best position of the neighborhood where the *i-th* search individual is located, $\vec{p}_{i,best}$, $\vec{g}_{i,best}$ are the constant between [0 1] of the best location φ_1, φ_2 ever experienced by *i-th* search individual; ω is the inertia weight, and then the position is updated to update each searcher position according to equation (6) and (7).

$$\Delta x_{ij}(t+1) = \alpha i_j(t) d_{ij}(t) \quad (6)$$

$$x_{ij}(t+1) = x_{ij}(t) + \Delta x_{ij}(t+1) \qquad (7)$$

Here, t $\rightarrow$ t + 1, if the stop condition is met, then the search is stopped. Otherwise, it moves forward.

$$\alpha_{ij}(t) \geq 0 \qquad d_{ij}(t) \in \{-1,0,1\} \qquad (8)$$

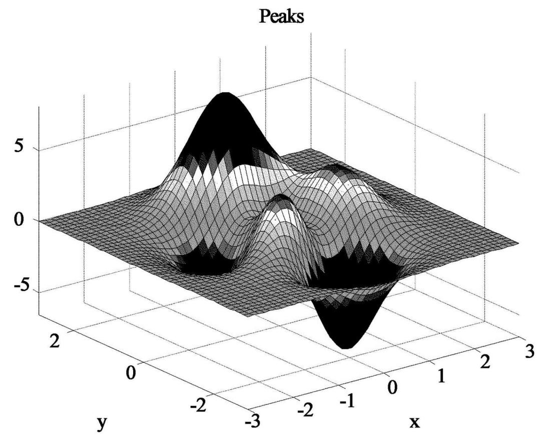

Figure 1. Function image

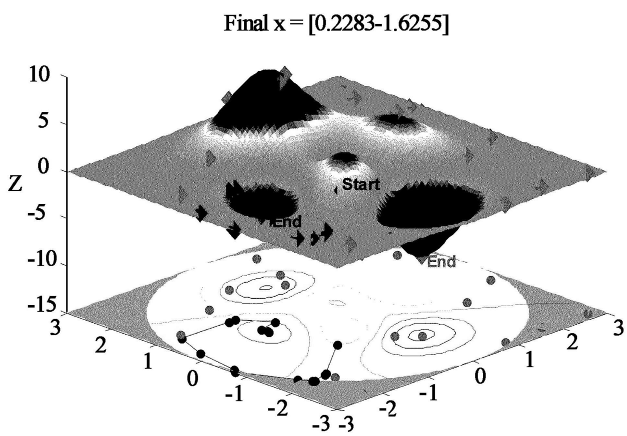

Figure 2. Optimization process diagram of SOA algorithm

3.3 Z - Score Optimization Model based on SQA

The excellent optimization ability of the SOA algorithm is used to make an effective optimization adjustment for the Z-Score model coefficients, so that it can be more accurate to forecast the financial risk of the listed companies in China. The specific algorithm flow is shown in Fig.3 If there are five unknown variables, respectively, which belong to $K_m K_z$, K: i, K,} K, so that the error of equation (9) is the lowest, and (9) is as follows:

$$Fitness(K) = Z_{实际} - Z_{预测} \qquad (9)$$

In equation 9, Z reality and Z predictions represent the Z-Score actual score and the Z-Score prediction score, respectively; the expressions are shown in equations 10 and 11, respectively:

$$Z_{实际} = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \quad (10)$$

$$Z_{预测} = K_1X_1 + K_2X_2 + K_3X_3 + K_4X_4 + K_5X_5 \quad (11)$$

X_1, X_2, X_3, X_4, and X_5 in equation 10 and equation 11 denote different financial indicators, respectively, as shown in equation (1).

4. Analysis and Discussion

4.1 An Empirical Analysis of Financial Data of Listed Companies

This paper chose the financial data of 20 listed companies as a research sample. Due to limited space, the Z-Score of 20 listed companies was calculated and compared with the data information contained in the tables, and it was known that only the financial situation of the first, the seventh, the ninth and the thirteenth listed companies met the standard. So, it can be found that the Z-Score model used in the past also has a relatively large adjustment space.

SOA algorithm parameter settings: population size, *sizepop* = 100, the maximum iterations Iteration = 100, the maximum membership value *Umax* = 0.9500, the minimum membership value Umin = 0.0111, the maximum weight *Wmax* = 0.9.

Serial number	X1	X2	X3	X4	X5	Y
1	0.017	0.182	0.4195	1.123	0.045	0
2	1.1202	0.1698	0.2648	0.8451	0.9654	1
3	0.2654	0.2314	0.5412	0.4215	0.0214	1
4	1.2514	0.2165	0.3214	1.0214	1.0321	1
5	0.3512	0.2154	0.2445	0.9844	0.9124	1
6	1.6215	0.3214	0.2654	1.0124	1.0321	1
7	1.1354	0.2155	0.3214	0.9874	0.5124	0
8	0.3512	0.2145	0.3214	0.1985	0.1346	1
9	0.8965	0.2145	0.2564	0.987	0.9541	0
10	0.5414	0.2654	0.2346	0.8425	0.0033	1
11	0.9541	0.214	0.1654	0.854	0.2157	1
12	0.0845	0.2677	0.2012	0.874	0.985	1
13	0.4451	0.2877	0.2114	0.564	0.217	0
14	0.8741	0.325	0.4115	0.1357	1.0146	1
15	0.4551	0.748	0.4645	0.557	0.8436	1
16	0.4687	0.2441	-0.543	-0.154	0.615	0
17	0.6173	0.311	0.1256	0.714	0.848	0
18	0.7541	0.2145	0.8445	0.548	0.844	1
19	0.4115	0.5178	0.2587	0.0257	0.548	0
20	0.1547	0.1235	0.3541	1.6574	1.214	1

Table 1. Financial Data of 20 Listed Companies

Serial number	Z-Score	Y
1	2.3214	0
2	3.6254	1
3	2.5412	1
4	4.9874	1
5	3.5412	1
6	4.5421	1
7	4.8745	0
8	2.5421	1
9	3.5576	0
10	2.7542	1
11	3.8136	1
12	2.5413	1
13	1.9542	0
14	4.1264	1
15	2.9465	1
16	1.2134	0
17	2.4324	0
18	3.8445	1
19	2.5457	0
20	3.2354	1

Table 2. Z-Score Values of 20 Listed Companies

As can be seen from the above table, with the increase of population size and iteration times, the ability of SOA algorithm to optimize Z-Score model parameters is stronger and faster, and can quickly get the optimal value, and the effect is good.

Serial number	Z-Score	SOA algorithm optimization Z-Score	Y
1	2. 3154	2.2267	0
2	3. 8251	4.4524	l
3	2. 1475	2.5624	l
4	4. 8254	4.9854	l
5	3. 1243	3.8457	l
6	4.6551	5.8544	l
7	4. 5412	4.8745	0
8	2. 1445	2.6571	1
9	3. 9845	4.2354	0
10	2. 5154	2.8745	1
11	3.5215	3.4151	1
12	2. 8457	2.9251	1
13	1.6012	1.7451	0
14	3. 8544	4.5412	1
15	3.4621	3.4654	1
16	1.3261	1.1687	0
17	2.8464	3.1046	0
18	3. 4658	4.4628	1
19	2.4289	2.7875	0
20	3. 4748	3.7456	1

Table 3. SOA Algorithm for 20 Listed Companies Optimize Z-Score Contrast Results

Z-Score model is optimized by SOA algorithm. When the fitness is the smallest, the corresponding model parameters K_1, K_2, K_3, K_4 and K_5 are 1.3204, 1.4531, 3.2482, 0.6751 and 1.1912 respectively. The average recognition rate of this algorithm is as high as 96.33%, which is much higher than that of the SVM algorithm and AdaBoost algorithm.

4.2 An Empirical Analysis of Financial Data of Case Enterprise

Using the financial data from the annual reports of Jiangsu Sainty Companies Limited by Shares from 2012 to 2016, the relevant indicators were calculated using the formula, as shown in Table 4.

Year	X1	X2	X3	X4	X5	Z
2012	0.0594	0.0367	0.0232	1.0847	0.8844	**1.7336
2013	0.0407	0.0421	0.0222	1.1459	1.1271	*1.9945
2014	-0.0940	0.0479	0.0416	0.7085	1.2311	**1.7464
2015	-0.1088	0.0824	0.0484	0.7719	2.0012	*2.6068
2016	-0.1266	0.1935	0.1616	0.8399	2.0315	3.1859

Table 4. The Parameters of Jiangsu Sainty Limited by Share Ltd Value

From the preceding table, we observe that between 2012 and 2016, the financial risk value Z of Sainty in Jiangsu Province showed poor performance, categorizing the company as a “high-risk enterprise” for four consecutive years. In 2003, the financial risk value Z of Sainty in Jiangsu Province improved from 1.7336 to 1.9945, reflecting a growth rate of 15.05%, and it transitioned from the initial bankruptcy zone to a grey area. Notably, X4 rose from 1.0847 to 1.1459, marking an increase of 5.64%; X5 grew from 0.8844 to 1.1271, demonstrating a rise of 27.44%. It can be stated that advancements in X4 and X5 significantly enhanced the Z value of financial risk, with X5 exerting a more pronounced influence. By applying the formula X5 = operating income/assets, it is clear that in 2013, the company’s total asset growth reached 5.31%, while its operating income surged by 34.21%. The substantial increase in operating income outpaced the overall asset growth, resulting in a significant rise in X5 and a notable improvement in the Z value of the company’s financial risk. This indicates that by 2013, the adverse effects of the global economic crisis sparked by the US subprime mortgage crisis were gradually diminishing. The traditional foreign trade sector was thriving, leading to a marked enhancement in total asset utilization efficiency.

Regarding 2014, the Z value of financial risk for Sainty in Jiangsu Province fell from 1.9975 in the previous year to 1.7463, reflecting a 12.34% decrease. Meanwhile, X4 dropped from 1.0435 to 0.7073, a decline of 43.63%; in contrast, X5 rose from 1.1263 the prior year to 1.2302, indicating an increase of 9.13%. The reduction in X4 coupled with the rise in X5 contributed to the decline in the Z value of the company’s financial risk, with X4 exerting a more significant impact. By using the formula X4 = total market value/liabilities, it can be observed that in 2014, the company’s overall market value decreased by 37.73% while liabilities rose by 0.72%. The substantial drop in the company’s total market capitalization suggested a lack of optimism in the capital market regarding the future of Jiangsu Sainty’s stock, leading to diminished investor confidence. The company’s capital structure appeared unreasonable, resulting in a Z value lower than in 2013 and an escalating financial risk. Consequently, even though the company remained in a precarious state, it slipped from the grey zone of 2013 in to an even more hazardous bankruptcy territory, with a notable deterioration in its financial risk condition.

In 2015, the Z score reflecting the financial risk of Sainty in Jiangsu Province rose from 1.7358 the previous year to 2.6075, marking an increase of 49.27%; the actual rise was even more significant, yet it remained within the grey area, not fully exiting the category of risky enterprises. Specifically, X4 increased from 0.7075 in the prior year to 0.7623, up 8.65%; X5 surged from 1.2342 last year to 2.0031, up 62.75%. The advancements in X4 and X5 contributed positively to the Z score of corporate financial risk, with X5 having a more substantial impact. Calculations reveal that the company's total assets fell by 8.31% in 2015, while operating income decreased by 3.45%, indicating that the drop in active income was less severe than the decrease in overall assets. This suggests that the asset utilization ratio of businesses improved compared to 2014, and the financial risk situation of the enterprise has been somewhat enhanced.

In 2016, the Z score for the financial risk of Sainty in Jiangsu Province increased from 2.6035 the previous year to 3.18642, signifying a rise of 23.42%. Its Z score surpassed the critical threshold of 2.99, allowing it to enter the safe zone. This marked the company's first exit from danger in five years. Notably, X1 decreased from -0.1045 the prior year to -0.1238, reflecting a drop of 16.43%; X2 rose from 0.0734 last year to 0.1823, an increase of 126.76%; X3 climbed from 0.0484 the previous year to 0.1672, showcasing a significant rise of 243.58%; and X5 grew from 2.0012 last year to 2.0315, with a 145% increase. Among these, only X1 displayed a downward trend; the increases in X2, X3, X4, and X5 substantially boosted the Z score of the company's financial risk, with X2 and X3 having particularly prominent effects. Analyzing the relevant data shows that as enterprises mitigate risk, the company's retained earnings and earnings before interest and taxes play crucial roles. The rise in X2 indicates the company's enhanced capacity to invest using retained earnings. The increase in X3 suggests that the company's total assets and profitability have also improved. With the influence of X2 and X3, Sainty's financial risk Z score in Jiangsu Province transitioned from a grey area to the safe zone, signifying a fundamental shift from a risky business to a secure enterprise.

Based on the analysis conducted earlier, it is evident that besides the influence of external macro-environmental factors, numerous internal elements contribute to the financial risk faced by foreign listed companies in China. These include inefficient asset use and an unreasonable distribution of profits. Therefore, utilizing the Z-score model, this paper undertakes an empirical study of various listed companies involved in foreign trade within China, and from the perspective of the enterprises themselves, proposes relevant strategies to mitigate financial risks: firstly, to establish a comprehensive financial risk control system linked to the Z-score model; secondly, to devise a rational income distribution strategy that ensures effective utilization of the company's retained profits; thirdly, to select suitable financing methods to optimize the capital structure of the enterprises; fourthly, to enhance the management capabilities regarding working capital; fifthly, to implement diverse strategies aimed at significantly boosting the company's profitability; and sixthly, to leverage the unique characteristics of listed companies effectively. In summary, it is crucial for our enterprises to significantly enhance their management standards and continuously provide positive signals to the market.

5. Conclusion

As the complexity of the market economy escalates, enterprises' financial risks are influenced by both external macro factors and internal micro factors. The uncertainties stemming from various internal and external influences place enterprises in financial jeopardy. Regardless of the type of business, a considerable financial risk increases the likelihood of a bankruptcy crisis. This situation can severely undermine the stable, healthy growth of the nation's economy. Given that the traditional Z-Score financial early-warning model has a low diagnostic rate, it is challenging to assess the financial risks of listed companies clearly. This paper selects the superior optimization capabilities of the SOA algorithm to be thoroughly integrated with the Z-Score financial early warning model, leading to the development of an optimized Z-Score financial early warning model. The fitness function for optimizing the Z-Score financial early warning model via the SOA algorithm is also established. Through simulation comparisons, it is demonstrated that the optimized Z-Score financial early warning model achieves an average recognition rate of 996.33%, substantially exceeding the average recognition rates of the SVN algorithm and the AdaBoost algorithm, significantly enhancing the financial predictive capabilities of the Z-Score economic early warning model and increasing its adaptability.

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