Enhancing the Fruit Fly Algorithm for Z-Score Financial Early Warning Models

Shianghau Wu[1], Jie Yu[2], Po-Jui Wu[3]*

[1] *Department of International Business, Chung Yuan Christian University, Taiwan*
[2] *School of Business, Macau University of Science and Technology, China*
[3] *School of Business, Macau University of Science and Technology, China*
antonwoo888@hotmail.com, yujiek2017@gmail.com, 2012raymondwu@gmail.com

Abstract

The purpose of this study was to enhance the accuracy of financial data prediction and decrease the root mean square error (RMSE) by improving the FOA algorithm and introducing the YJFOA Z-score model. The financial data of 29 ST companies (including *ST) listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange and 29 non-ST companies in the Yangtze River Delta from 2015 to 2019 were analyzed using the optimized Z-score model based on the new YJFOA-ZSCORE model. By enhancing the Fruit Fly algorithm's performance, the study discovered the limitation of the traditional Z-score model in evaluating the financial situations of Chinese A-share listed companies. As a result, a suitable threshold was identified to create a new financial early warning system. The study concluded that the new YJFOA Z-score model outperformed the FOA-ZSCORE and PSO-ZSCORE models in predicting all types of companies.

Keywords: Z-score model, Fruit Fly Algorithm, Optimization, Financial early warning model, PSO algorithm

1 Introduction

In 1968, Altman introduced the traditional Z-score model [1], a financial analysis tool that gathered data from both bankrupt and non-bankrupt manufacturing companies in the United States. This model utilized a variety of financial ratios, employing mathematical statistics to select and elucidate five key financial factors. However, given its 1968 release, the traditional Z-score model's predictive accuracy might be compromised by changes in temporal and spatial contexts. To address this, algorithms can be applied to enhance Z-score models.

Various optimization algorithms designed for solving complex problems in computer science and operations research include the Fruit Fly Algorithm (FOA), Adaptive Large Neighborhood Search (ALNS), Tabu Search, Red Deer Algorithm, and Social Engineering Optimizer, each tailored to address specific optimization challenges.

The Fruit Fly Algorithm (FOA), inspired by fruit fly foraging behavior, applies a swarm intelligence approach, prioritizing exploration over exploitation within the search space. Adaptive Large Neighborhood Search (ALNS) is a flexible metaheuristic, modifying its strategy based on problem characteristics and implementing a "destroy and repair" tactic. Tabu Search, a traditional metaheuristic, focuses on local search while avoiding local optima [2-3]. The Red Deer Algorithm simulates communication and adaptation among agents, suitable for dynamic and multi-objective optimization scenarios. The Social Engineering Optimizer draws inspiration from social behaviors for problem-solving.

Choosing the optimal optimization algorithm depends on factors like problem type and characteristics, necessitating careful evaluation of each algorithm's suitability for a specific task.

Pan [4] proposed the Fruit Fly Algorithm (FOA), a global optimization algorithm. When combined with the traditional Z-score model, it led to the FOA-ZSCORE model. However, issues of instability and partial equilibrium arose. To address these, the study introduced the YJFOA-ZSCORE model, enhancing prediction accuracy when analyzing financial data from 29 ST and non-ST companies in the Yangtze River Delta from 2015 to 2019. The YJFOA-ZSCORE model outperformed the FOA-ZSCORE and PSO-ZSCORE models for predicting all types of companies.

As the Chinese economy developed, the Yangtze River Delta Economic Zone gained importance. Limited research on financial early warning analysis in this region prompted the study, utilizing the CSMAR database for ST and non-ST companies [5-7]. The study identified limitations in the traditional Z-score model for Chinese A-share listed enterprises and proposed a suitable threshold for a new financial early warning system. The paper emphasizes the need for a reasonable financial early warning model to provide timely risk warnings and informed decision-making by senior executives.

2 Literature Review

The Z-score model, pioneered by Altman in 1968, stands as a renowned financial early warning system. This model, leveraging financial ratios and mathematical statistics from both bankrupt and non-bankrupt U.S. production companies, constructs a metric known as the Z value. A Z value less than 1.8 signifies a company in the bankruptcy zone, while

*Corresponding Author: Shianghau Wu; E-mail: antonwoo888@hotmail.com
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1.8-2.99 indicates financial crisis, and anything above 2.99 suggests a sound financial standing. Despite its success in some regions, studies show varied results in different countries. In Greece, Gerantonis et al. found a prediction success rate of only 54%, impacting forecast accuracy [8]. Similarly, Meeampol et al. noted fluctuations in accuracy in Thailand's stock market, necessitating further research for market suitability [9]. Altman's application in Italy yielded high prediction accuracy, reaching 90% with adjustments [10-11]. MacCarthy's analysis in Ghana revealed a 79.9% success rate using the Z-score model [12].

In China, Zhang and Zhu's study on technology-listed companies highlighted a discrepancy between non-ST and ST listed companies, with the latter facing financial issues [13]. However, the study identified instances of Z values being too high, leading to a failure in the early warning model, aligning with Wu et al.'s concern about misleading results due to Z-score parameters [14].

Scholars have proposed algorithmic adjustments to enhance the Z-score model's accuracy and stability. Cao et al. utilized the ID3 algorithm and BP neural network to achieve higher prediction accuracy than the traditional model [15]. Other studies have explored algorithms like the fruit fly algorithm, demonstrating its effectiveness in optimizing Z-score parameters [16-17]. Lepetit and Strobel's time-varying Z-score model and Zhao and Hou's revision based on the cash flow statistical method also aimed at improving accuracy [18-23]. Kang et al. optimized Z-score parameters using the fruit fly algorithm, resulting in increased prediction success rates [24].

In summary, the Z-score model exhibits varying success rates globally, with higher accuracy in certain countries and industries. The fruit fly algorithm emerges as a simple and fast optimization tool, although it has limitations. To address these, scholars have explored diverse algorithms and methods, such as the ID3 algorithm, BP neural network, coefficient time-varying, and generalized regression neural network, to enhance the fruit fly algorithm.

Notably, there is limited research on financial early-warning analysis in the Yangtze River Delta [25]. The existing literature primarily focuses on foreign trade companies, emphasizing the need for more comprehensive studies on enterprises in this region. As the Z-score model continues to evolve and adapt through algorithmic enhancements, ongoing research and tailored applications are crucial for accurate financial predictions and risk management.

3 Research Method

3.1 The Traditional Z-score Method

Altman proposed the traditional Z-score model, which comprehensively assesses a company's asset scale, liquidity, operating capacity, and debt solvency. In this model, Z represents the Z-value. A higher Z value indicates a lower probability of company bankruptcy, while a lower Z value indicates a greater probability of bankruptcy. The following formula is the definition of the model [10]:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 . \quad \textbf{(1)}$$

X1 represents the company's asset scale and liquidity, calculated as working capital divided by total assets. X2 represents the company's profitability, calculated as retained earnings divided by total assets. X3 represents the production capacity of corporate assets (excluding taxation and financing), calculated as EBIT divided by total assets. X4 represents the relative relationship between shareholders and creditors, indicated by the market value of shareholder's equity divided by the book value of total liabilities. X5 represents the company's ability to generate sales using its assets, calculated as total sales divided by total assets.

In general, when the Z value is below 1.8, the enterprise faces a bankruptcy crisis. If the Z value falls between 1.8 and 2.675, it falls within the gray area where it becomes challenging to determine the likelihood of bankruptcy. If the Z value exceeds 2.675, it indicates good financial performance and a reduced probability of bankruptcy for the enterprise.

3.2 The Z-score Model Optimized by The Fruit Fly Algorithm (FOA-ZSCORE)

The traditional Z-score may not be applicable to all countries, regions, or industries. Additionally, the model's parameter term remains unchanged based on the sample data, and the range of Z-values is not adjusted according to temporal and spatial conditions. Consequently, there is a problem of low prediction accuracy. For instance, Zhou and Pang discovered that the predicted Z-value had a higher accuracy rate for ST companies but a lower accuracy rate for non-ST companies [26]. Similarly, Zhang and Zhu observed that even though some ST companies faced significant financial issues, the traditional Z-score model yielded higher Z-values, rendering the early warning system ineffective [13].

Pan introduced the Fruit Fly Algorithm (FOA), a global optimization algorithm inspired by the foraging behavior of fruit flies [4]. The algorithm was combined with the traditional Z-score model to create the FOA-ZSCORE model. Fruit flies can detect and gather airborne odors to find food or other insects. They rely on their sharp vision to navigate towards their target. As for the benchmark instances, this method finds practical use in various real-world scenarios, including optimizing functions, enhancing the precision of financial crisis warnings for businesses, improving generalized regression neural networks, and optimizing PID parameters [27].

The traditional Z-score model is unable to adapt to actual samples since its parameters are fixed and cannot be universally applied. In contrast, the FOA-ZSCORE model addresses this limitation by utilizing the fruit fly algorithm (FOA). By considering the specific circumstances of the sample, the FOA-ZSCORE model generates new constant terms (a1, a2, a3, a4, a5) and utilizes them to construct a new and improved model. As a result, the root mean square error (RMSE) and prediction accuracy of the new model are enhanced.

The optimization process of the new model is as follows:

$$Z^{*} = a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 . \quad \textbf{(2)}$$

Step 1: Generate an initial group of fruit flies randomly, and set the generation range of the group of fruit flies between [0,1]

$$\text{Init X\_axis} . \quad (3)$$

$$\text{Init Y\_axis} . \quad (4)$$

Step 2: Give the individual fruit fly a random direction and distance to search for food. The random range set by FOA-ZSCORE is [-1,1].

$$X_i\text{=X\_axis+(2*Random value-1)} . \quad (5)$$

$$Y_i\text{=Y\_axis+(2*Random value-1)} . \quad (6)$$

Step 3: As the fruit fly lacks the ability to determine the location of food, it becomes essential to initially acquire the distance (Dist) between the fruit fly and the origin. Based on this distance, the judgment value (S) of taste concentration is calculated, which is essentially the inverse of the distance. However, in the case of FOA-ZSCORE, which comprises five independent variables, the Dist function needs to be executed five times, along with the corresponding taste concentration judgment value function. Each independent variable is associated with the value of the previous parameter for concentration. Dist function and related variables were defined as follows:

$$Dist_i = \sqrt{X_i^2 + Y_i^2} \ . \quad (7)$$

$$S_i = \frac{1}{Dist_i} \ . \quad (8)$$

$$a_i = S_i \ . \quad (9)$$

Step 4: Bring the new parameters (a1, a2, a3, a4, a5) into the original sample data, and then calculate the observed value. The root mean square error (RMSE) was calculated by the observed and actual values. In this step, the root mean square error is set as a function of taste concentration.

$$Smellfunction = RMSE = \sqrt{\frac{(OB - NV)^2}{n}}. \quad (10)$$

In this step, OB was the observed value calculated by the algorithm, NV is the actual value of the sample, and n is the sample size.

Step 5: Find the fruit flies with the lowest taste concentration in the fruit flies group (minimum smell function).

$$\text{[bestSmell bestIndex]=min(Smell)} . \quad (11)$$

Step 6: The fruit flies use their vision and sense of smell to fly to the coordinate axis of the best taste concentration value, and save the X and Y coordinates of the best taste concentration value:

$$\text{Smellbest=bestSmell} . \quad (12)$$

$$\text{X\_axis=X(bestIndex)} . \quad (13)$$

$$\text{Y\_axis=Y(bestIndex)} . \quad (14)$$

Step 7: We use the FOA-ZSCORE model to make the iterative optimization, and repeat steps 2 to 5, if the taste concentration is better than the previous generation taste concentration, then go to step 6. And we continued the above-mentioned steps until the maximum number of iterations (Max_gen). Figure 1 showed the iterative process of the fruit fly algorithm:

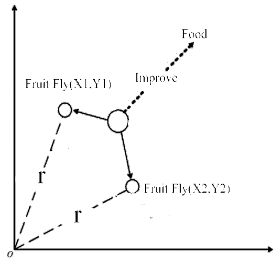

Figure 1. Iterative process diagram

However, in most cases, the fruit fly algorithm (FOA) used in the FOA-ZSCORE model encounters issues of instability and partial equilibrium. The instability arises from the random generation of the initial population of fruit flies within the range of [0,1] in the algorithm. As subsequent iterations of fruit flies also undergo randomization within the range of [-1,1], the resulting random radius does not align with the actual sample. When the maximum number of iterations (Max_gen) is exceeded, the optimal value of taste concentration, measured by the root mean square error (RMSE), tends to be larger. This problem is compounded by local optimization, where even if the results initially yield a lower RMSE, they may become stuck in local optimization. In this state, the algorithm continuously searches for the coordinates of the so-called optimal taste concentration value but fails to reach the global optimum. This limitation represents a drawback of the FOA algorithm.

3.3 The Improved Fruit Fly Algorithm Optimization Model (YJFOA-ZSCORE)

This study aimed to enhance the algorithm and propose a new model called YJFOA-ZSCORE. This article will outline the initial improvement ideas and the final improvement ideas.

Step 1: To address the instability of the fruit fly algorithm, the YJFOA-ZSCORE model utilized a dynamic step size method by adjusting the step radius. The radius function, denoted as R, was modified based on the best taste value. The coefficient C of Smellbest was determined by calculating the average value of the financial leverage indicators X1, X2, X3, X4, and X5 from the real sample (0.55 in this paper). The constant 0.15 was determined through multiple program iterations. Local optimum refers to the situation where the algorithm identifies a range, but the objective function fails to reach the global optimum. To overcome this limitation, the optimization algorithm incorporated the radius coefficient R, gradually reducing the search radius to achieve the overall optimum.

Step 2: Each individual fruit fly was assigned a specific direction and distance to search for food. In YJFOA-ZSCORE, the random range is set as [-R, R].

$$\begin{cases} R = 0.55 * Smellbest,\ Smellbest \geq 1 \\ R = 0.15 * Smellbest,\ Smellbest < 1. \end{cases} \quad \textbf{(15)}$$

$$Y_i = Y\_axis + R*(2*\text{Random value}-1)\ . \quad \textbf{(16)}$$

$$X_i = X\_axis + R*(2*\text{Random value}-1)\ . \quad \textbf{(17)}$$

The subsequent steps followed the same process as the FOA-ZSCORE model. This optimization method effectively addressed the instability issues of the fruit fly algorithm by dynamically adjusting the random radius based on the optimal taste value of each iteration. However, the problem of local optimization persisted, with the RMSE only reaching approximately 0.2. To overcome this issue, it is necessary to modify the trigger condition for step adjustment. Our observations revealed that fruit flies encountered local optimization problems around the 25th iteration, which is approximately one-fourth of the maximum number of iterations. Even when we increased the maximum number of iterations, the problem remained unresolved. Consequently, we explored the possibility of altering the trigger condition for the dynamic radius adjustment. The result of the change is as follows:

$$\begin{cases} R = 0.15 * Smellbest, gen \geq 0.25 * (\max\_gen) \\ R = 0.55 * Smellbest, gen < 0.25 * (\max\_gen). \end{cases} \quad \textbf{(18)}$$

$$Y_i = Y\_axis + R*(2*\text{Random value}-1)\ . \quad \textbf{(19)}$$

$$X_i = X\_axis + R*(2*\text{Random value}-1)\ . \quad \textbf{(20)}$$

If the number of iterations exceeded or equaled 0.25 times the maximum number of iterations, the search range would be narrowed with a coefficient of 0.15. However, if the number of iterations was below 0.25 times the maximum number of iterations, we expanded the search range. The purpose was to allow the results to encounter local optimization beforehand, and then, by reducing the search radius, the fruit flies would gradually approach the minimum value of the RMSE. This adjustment significantly enhanced the model's fit. The remaining steps of the algorithm were performed in the same manner as the FOA-ZSCORE model.

3.4 Data Collection

Based on relevant literature and model assumptions, our data spanned from 2015 to 2019 and included companies registered within the Yangtze River Delta region. Specifically, we focused on ST companies (representing listed companies with poorer financial performance) and non-ST listed companies from either the Shenzhen Stock Exchange or the Shanghai Stock Exchange. However, during the actual process of collecting samples, we encountered the possibility of extreme values or missing data.

Both the number of ST listed companies and non-ST listed companies were equal, and their registration locations, industry classification codes, and classification names had to match. Additionally, both types of companies had to be located in the same city or province. We specifically selected ST companies with extreme values of financial leverage and Z-value. The cutoff date for obtaining financial data was December 31, 2019. This decision was influenced by the impact of the COVID-19 pandemic on the data for the year 2020.

4 Results and Discussion

4.1 The Traditional Z-score Model

We used the financial data of 29 non-ST companies and 29 ST companies from 2015 to 2019 (58 companies in total) to construct the traditional Z-score model. The descriptive statistics were listed in Table 1 and Table 2.

Table 1. Descriptive statistics of 29 ST companies

Variable	X1	X2	X3	X4	X5	Z-Value
Mean	0.032	-0.608	-0.093	2.157	0.549	0.722
Median	0.161	0.036	0.018	0.990	0.382	1.388
Max	0.701	0.4646	4.736	42.494	6.856	26.270
Min	-9.208	-18.44	-3.749	-0.904	0.015	-33.835
Std	1.020	2.523	0.69	4.407	0.793	6.086
No. Sample	29	29	29	29	29	29

Table 2. Descriptive statistics of all companies

Variable	X1	X2	X3	X4	X5	Z-Value
Mean	0.1355	-0.266	-0.029	1.983	0.779	1.661
Median	0.2168	0.103	0.036	1.156	0.521	1.728
Max	0.7013	0.464	4.736	42.49	11.41	26.27
Min	-9.2089	-18.44	-3.749	-0.904	0.0153	-33.83
Std	0.744	1.84	0.500	3.399	1.370	4.631
No. of Sample	58	58	58	58	58	58

Table 1 reveals that, based on the traditional Z-score model, the average Z-value of ST listed companies in the Yangtze River Delta over the five-year period is 0.7228, with a median of 1.3887. These values are below the threshold of 2.675. The standard deviation of the Z-values for this group of samples is 6.0868, indicating a relatively larger distribution of Z-values among ST companies during the five-year period. This larger distribution contributes to the instability of the traditional Z-score model. Specifically, indicators X2 and X4 have higher standard deviations, suggesting that ST companies face a higher risk of bankruptcy due to their difficulties in managing insolvency.

Table 2 provides insights into the entire sample. The average Z-value for the entire sample decreased from 2.6002 in the non-ST group to 1.6615, primarily due to the influence of extreme values in the ST group. The maximum and minimum values of the entire sample align with those of the ST group samples. The standard deviation is 4.6319, indicating that the descriptive statistics of all companies are heavily influenced by those of the ST group. However, the traditional Z-score model lacks the ability to adapt its parameters to changes in samples, which inevitably impacts its prediction results to some extent. Table 3 presents the distribution of Z-values for reference.

From Table 3, we can conclude that the proportion of *ST companies with Z-values less than 1.8 increased from 29.41% in 2015 to 94.12% in 2018. However, this proportion declined in 2019. As for ST companies, although their financial risk is lower than *ST companies, we observed that many ST companies had Z-values below 1.8 from 2015 to 2019, with proportions ranging from 50% to 75%. This indicates a deterioration in the financial structure of these companies and an increase in financial risks. The number of ST companies falling within the range of [1.81, 2.675] remained consistently at 2 to 3 companies, with their proportion remaining largely unchanged.

Regarding non-ST companies, the number of companies with Z-values below 1.8 increased over the years, with the proportion rising from 41.38% to 44.83%. Furthermore, from 2015 to 2017, the number of non-ST companies with Z-values in the range of [1.81, 2.675] continued to increase. Almost half of the non-ST companies had Z-values below the threshold of 2.675, indicating that the traditional Z-score model may lead to misjudgment in real-world conditions due to the abnormal distribution of Z-values. The prediction results of the traditional Z-score model are presented in Table 4.

Table 3. Z Value distribution

Type of enterprise	Z-Value	Z<1.8		1.81<Z<2.675		Z>2.675	
	Year	Number	Percentage	Number	Percentage	Number	Percentage
*ST company	2015	5	29.41%	7	41.18%	5	29.41%
	2016	6	35.29%	7	41.18%	4	23.53%
	2017	11	64.71%	4	23.53%	2	11.76%
	2018	16	94.12%	1	5.88%	0	0.00%
	2019	13	76.47%	0	0.00%	4	23.53%
ST company	2015	6	50.00%	3	25.00%	3	25.00%
	2016	8	66.67%	3	25.00%	1	8.33%
	2017	7	58.33%	3	25.00%	2	16.67%
	2018	8	66.67%	2	16.67%	2	16.67%
	2019	9	75.00%	3	25.00%	0	0.00%
Non-ST company	2015	12	41.38%	4	13.79%	13	44.83%
	2016	12	41.38%	8	27.59%	9	31.03%
	2017	10	34.48%	10	34.48%	9	31.03%
	2018	13	44.83%	8	27.59%	8	27.59%
	2019	13	44.83%	6	20.69%	10	34.48%

Table 4. Accurate prediction rate of the traditional Z-score model

Year	2015	2016	2017	2018	2019
The number of companies correctly predicted	34	33	34	35	35
Accurate prediction rate (%)	58.62	56.90	58.62	60.34	60.34

Between 2015 and 2017, the traditional Z-score model exhibited an accurate prediction rate of less than 60%. However, from 2018 to 2019, the accuracy improved and surpassed 60%. Nevertheless, we noticed that the majority of non-ST companies had low Z-values according to the traditional Z-score model. This observation can be attributed to two possible reasons. First, non-ST companies may indeed have financial risks. Second, the coefficients used in the traditional Z-score model may not be adaptable to the real conditions of listed companies in the Yangtze River Delta, leading to misclassification of many companies. Unfortunately, the traditional Z-score model is unable to address this issue as the coefficients are fixed and cannot be adjusted. In our view, there is a need for improvements to the traditional Z-score model to resolve this problem.

4.2 The Z-score Model Optimized by The Fruit Fly Algorithm (FOA-ZSCORE)

To address the fixed coefficient terms and lower accurate prediction rate of the traditional Z-score model, this study utilized the FOA-ZSCORE model as a potential solution. FOA involves setting and tuning several parameters to achieve desirable performance. The following are the main parameters in FOA and guidelines for their selection and tuning: (1) Population size (2) Judgment value (S) (3) Randomness parameter (4) Distance function (5) Maximum iterations. The maximum number of iterations (Maxgen) was set to 100, and the population size (Sizepop) was set to 70. After running the program for 100 iterations, the optimal root mean square error (RMSE) was determined to be 0.4408. The figures below illustrate the optimization process diagram of the model and the flight path diagram of the fruit flies.

Based on Figure 2 and Figure 3, we can conclude that the FOA-ZSCORE model achieved convergence after the 83rd iteration and yielded an RMSE of 0.4408. However, between the 35th and 80th iterations, the optimization process stagnated, indicating a period of local optimization. Figure 3 also reveals that the optimal range for the X-axis coordinates was between -2.5 and 2, while the optimal range for the Y-axis coordinates was between 0 and 2. These ranges differ from the coordinate range observed in our actual sample. By applying the taste concentration function, we were able to determine the coefficients of the FOA-ZSCORE model. The optimal coefficients are provided in Table 5.

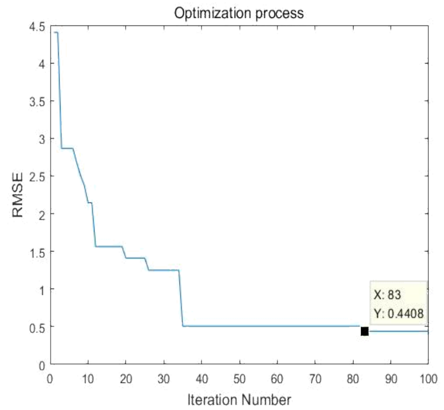

Figure 2. FOA-ZSCORE optimization process diagram

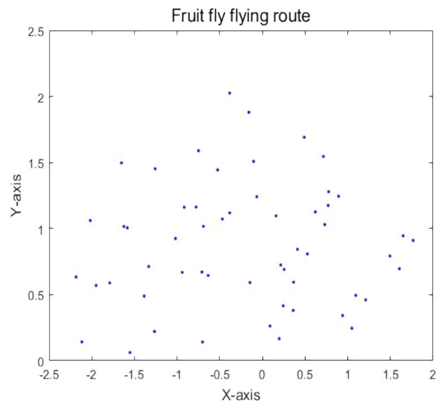

Figure 3. Fruit flies flight path

Table 5. Optimal coefficient value of FOA-ZSCORE model

Coefficient	a1	a2	a3	a4	a5
The optimal value	1.0127	1.1185	2.1986	0.5882	0.7071

The FOA-ZSCORE model was as follows:

$$Z^{FOA*} = 1.0127X_1 + 1.1185X_2 + 2.1986X_3 + 0.5882X_4 + 0.7071X_5. \quad (21)$$

The descriptive statistics of coefficients in FOA-ZSCORE model results were shown in Table 6:

Our analysis revealed that the FOA-ZSCORE model demonstrated improvements compared to the traditional Z-SCORE model. The average Z-value of the FOA-ZSCORE model decreased from 1.6615 to 1.4921, while the median decreased from 1.7284 to 1.4516. Additionally, the standard deviation decreased from 4.6319 to 3.8148. These findings suggest that the Z-values obtained from the FOA-ZSCORE model were generally lower and exhibited greater stability with fewer outliers when compared to the traditional Z-SCORE model. The maximum and minimum Z-values obtained from both models remained the same, originating from *ST bus (002188.SZ) and *ST Baoqian (600074.SH). However, the upper and lower boundaries of the Z-values decreased from Table 7. Z-Value Distribution Table (FOA-ZSCORE) [-33, 26] to [-27, 25] in the FOA-ZSCORE model. This adjustment better reflected the actual financial status of our sample, enhancing the model's accuracy. To further validate the prediction accuracy of the FOA-ZSCORE model, we utilized the sample data for calculations, and the results are presented in Table 7.

Table 6. Data of full companies (FOA-ZSCORE)

Variable	X1	X2	X3	X4	X5
Mean	0.1355	-0.2662	-0.0298	1.9835	0.7798
Median	0.2168	0.1038	0.0363	1.1563	0.5219
Max	0.7013	0.4646	4.7364	42.4943	11.4156
Min	-9.2089	-18.441	-3.749	-0.9047	0.0153
Std	0.744	1.84	0.5007	3.399	1.3709
No. Sample	58	58	58	58	58

Table 7. Z-Value distribution table (FOA-ZSCORE)

Type of enterprise	Z-Value	Z<1.8		1.81<Z<2.675		Z>2.675	
	Year	Number	Percentage	Number	Percentage	Number	Percentage
*ST company	2015	7	41.18%	5	29.41%	5	29.41%
	2016	8	47.06%	5	29.41%	4	23.53%
	2017	14	82.35%	1	5.88%	2	11.76%
	2018	16	94.12%	1	5.88%	0	0.00%
	2019	13	76.47%	0	0.00%	4	23.53%
ST company	2015	7	58.33%	3	25.00%	2	16.67%
	2016	10	83.33%	1	8.33%	1	8.33%
	2017	10	83.33%	0	0.00%	2	16.67%
	2018	9	75.00%	1	8.33%	2	16.67%
	2019	11	91.67%	1	8.33%	0	0.00%
Non-ST company	2015	13	44.83%	7	24.14%	9	31.03%
	2016	16	55.17%	6	20.69%	7	24.14%
	2017	16	55.17%	5	17.24%	8	27.59%
	2018	16	55.17%	5	17.24%	8	27.59%
	2019	15	51.72%	7	24.14%	7	24.14%

Table 8. Accurate prediction rate of FOA-ZSCORE model

Year	2015	2016	2017	2018	2019
Number of companies accurately predicted	31	31	33	35	32
Accurate prediction rate (%)	53.45	53.45	56.90	60.34	55.17

Based on Table 7, the prediction accuracy rates for *ST listed companies were 41.18%, 47.06%, and 82.35% from 2015 to 2018. These rates were higher than those of the traditional Z-score model. However, non-*ST companies often have Z-scores below 1.8, which results in a decrease in prediction accuracy. Some non-*ST companies had Z-scores ranging from 1.81 to 2.675. The new model's Z-scores for non-*ST companies did not reach the 2.675 threshold for financial stability. This inevitably impacted the overall prediction accuracy since non-*ST companies accounted for 50% of the total sample. Table 8 provides the accurate prediction rates for the new model.

The decrease in prediction accuracy occurred because both ST companies and non-ST companies experienced a decline in their Z-values based on the FOA-ZSCORE results. However, we also observed that the new model improved the accurate prediction rate for ST companies. This indicates that the FOA-ZSCORE model was more sensitive to samples with small values. However, when the sample value increased, the Z-values would decrease due to local optimization. To address this issue, our intention was to reduce the RMSE value of the model in order to enhance its performance.

4.3 PSO Algorithm Model

The PSO algorithm is based on the social behavior of birds in flocks. In this algorithm, individuals are represented as particles and move in a three-dimensional space [28]. The particles' positions in the search path are updated based on individuals' tendency to outperform others. The search model's results indicate that the process continues until individuals return to previously successful areas. The velocity (v) and position (x) of each particle are modified using the following equations [29]:

$$v_{ij}(t+1) = wv_{ij}(t) + c_1 r_1 (pB_{ij}(t) - x_{ij}(t)) + c_2 r_2 (gB_{ij}(t) - x_{ij}(t)); \quad \textbf{(22)}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad . \quad \textbf{(23)}$$

In the PSO algorithm, $V_{ij}(t+1)$ represents the velocity of particle i at iteration j, and $x_{ij}(t+1)$ represents its position. The inertia weight, denoted as w, is used to control the influence of the previous velocity record. The variable t represents the number of iterations, c1 is the cognition learning factor, c2 is the social learning factor, and r1 and r2 are random numbers between 0 and 1 that represent the ability to remember information. The value of v is constrained within the range $[-V_{max}, V_{max}]$ to prevent the particle from wandering excessively outside the search space. The PSO algorithm terminates either after a certain number of generations or when a particle reaches its best position without any further improvement [30]. The PSO algorithm uses several parameters, including the number of particles, c1, c2, w, and termination criteria that need to be set and tuned to achieve optimal performance.

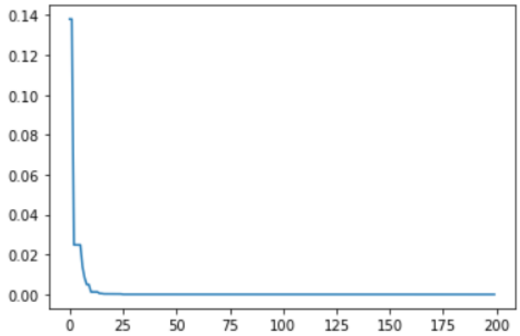

Figure 4. PSO optimization process diagram

The study used the PSO algorithm to optimize the parameters of the variables in the Z-score model. We set the maximal iterations as 100, the number of population as 70, w as 0.8, and c1 and c2 as 0.5. The RMSE was obtained after 100 iterations was 1.1857*e-15. Figure 4 showed the optimization process diagram of the model. The horizontal axis indicates the iteration number and the vertical axis indicates the RMSE value.

According to Figure 4, the RMSE values were on the vertical axis. It indicated that the RMSE was converged before the 20 iterations. The coefficient of PSO Z-score model can be obtained, and the optimal coefficient was as Table 9:

Table 9. Optimal coefficient value of PSO Z-score model

Coefficient	a1	a2	a3	a4	a5
The optimal value	3.247	0.1732	1.2735	0.5716	3.4089

The PSO Z-score model was as follows:

$$Z^{PSO*} = 3.247X_1 + 0.1732X_2 + 1.2735X_3 + 0.5716X_4 + 3.4089X_5. \quad \textbf{(24)}$$

We also used the financial data of 29 non-ST companies and 29 ST companies from 2015 to 2019 (58 companies in total) and constructed the traditional Z-score model. Table 10 and Table 11 were the descriptive statistics of all companies and the Z-value distribution.

Table 10. Descriptive statistics of all variables

Variable	X1	X2	X3	X4	X5	Z-value
Mean	0.135	-0.26	-0.02	1.983	0.779	3.008
Median	0.216	0.103	0.036	1.156	0.521	2.553
Max	0.701	0.464	4.736	42.49	11.41	39.67
Min	-9.20	-18.4	-3.74	-0.90	0.015	-33.81
Std	0.744	1.84	0.500	3.399	1.370	6.389
No. of sample	58	58	58	58	58	58

Table 11. Z-value distribution table

Type of Enterprise	Z-Value	Z<1.8		1.81<Z<2.675		Z>2.675	
	Year	Number	Percentage	Number	Percentage	Number	Percentage
*ST company	2015	2	11.46%	4	23.53%	11	64.71%
	2016	5	29.41%	1	5.88%	12	70.59%
	2017	7	41.18%	1	5.88%	8	47.06%
	2018	16	94.12%	1	5.88%	0	0.00%
	2019	13	76.47%	0	0.00%	4	23.53%
ST company	2015	1	8.33%	6	50.00%	5	41.67%
	2016	4	33.33%	3	25.00%	4	33.33%
	2017	5	41.67%	3	25.00%	5	41.67%
	2018	8	66.67%	2	16.67%	2	16.67%
	2019	9	75.00%	3	25.00%	0	0.00%
Non-ST company	2015	3	10.34%	3	10.34%	23	79.31%
	2016	4	13.79%	1	3.45%	24	82.76%
	2017	10	34.48%	10	34.48%	9	31.03%
	2018	13	44.83%	8	27.59%	8	27.59%
	2019	13	44.83%	6	20.69%	10	34.48%

According to Table 10, the mean and median Z-values were larger than that of traditional and FOA Z-scores model. It indicated that the Z-scores were overestimated.

In Table 11, the Z values of PSO results were higher for *ST and ST companies from 2015 to 2017, and it resulted in the lower accurate prediction rate for *ST and ST companies. Meanwhile, the Z-scores of the non-ST companies were lower from the years of the 2017 to 2019.

According to Table 12, we found that the overall accurate prediction rate gradually increased from 2015 to 2018. However, the overall accurate prediction rate decreased in 2019.

Table 12. Accurate prediction rate of the PSO Z-score model

Year	2015	2016	2017	2018	2019
The number of companies correctly predicted	29	34	37	42	39
Accurate prediction rate (%)	50.00	58.62	63.79	72.41	67.24

4.4 The Improved Fruit Fly Algorithm Optimization Model (YJFOA-ZSCORE)

We used the identical research setup, software, and samples as described in the previous section to assess the performance of the new YJFOA-ZSCORE model. Through 100 iterations, we successfully attained an optimal RMSE value of 0.06163. Figure 5 illustrates the optimization process, while Figure 6 displays the flight path of the fruit flies.

We observed that the YJFOA-ZSCORE model achieved convergence during the 39th generation iteration, resulting in a value of 0.06163. Analyzing Figure 6 reveals that the flight path of the fruit flies differed from that of the FOA models. In the case of the fruit flies, their trajectory appeared more scattered, while the improved FOA algorithm exhibited a flight path with a greater concentration of fruit flies. The optimal coordinate range along the X-axis was found to be between [-1, 0.2], and along the Y-axis, it was between [-0.2, 1.8]. These ranges were smaller than those of the FOA-ZSCORE model. The coefficients for the YJFOA-ZSCORE model are listed in Table 13.

The YJFOA algorithm used radius, randomness value, distance function and the judgement value (S) as the main parameters and guidelines for their selection and tuning.

Compared with the coefficients of the YJFOA-ZSCORE model and that of the FOA-ZSCORE model, the coefficients of the YJFOA-ZSCORE model were larger, and the Z values were in a suitable range. The descriptive statistics of the whole sample were as Table 14:

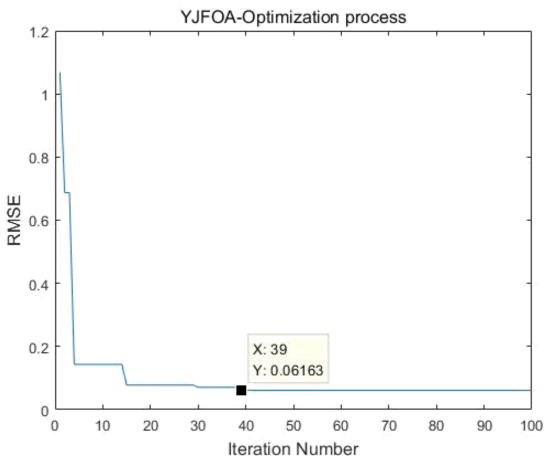

Figure 5. YJFOA-ZSCORE optimization process diagram

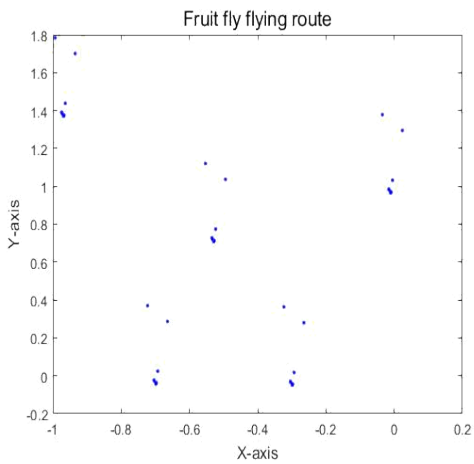

Figure 6. Fruit flies flying path of YJFOA-ZSCORE model

Table 13. Optimal coefficients value YJFOA-ZSCORE model

Coefficient	a1	a2	a3	a4	a5
The optimal value	1.1364	1.4379	3.3461	0.5968	1.0369

Table 14. Data of full sample (YJFOA-ZSCORE)

Variable	X1	X2	X3	X4	X5	Z-Value
Mean	0.135	-0.266	-0.029	1.983	0.779	1.6639
Median	0.216	0.103	0.036	1.156	0.521	1.7325
Max	0.701	0.464	4.736	42.49	11.41	26.142
Min	-9.208	-18.44	-3.749	-0.904	0.015	-33.81
Std	0.744	1.84	0.500	3.399	1.370	4.6672
no. of sample	58	58	58	58	58	58

Table 15. Z value distribution table (YJFOA-ZSCORE)

Type of enterprise	Z-Value	Z<1.8		1.81<Z<2.675		Z>2.675	
	Year	Number	Percentage	Number	Percentage	Number	Percentage
*ST company	2015	5	29.41%	5	29.41%	7	41.18%
	2016	6	35.29%	7	41.18%	4	23.53%
	2017	11	64.71%	4	23.53%	2	11.76%
	2018	16	94.12%	1	5.88%	0	0.00%
	2019	13	76.47%	0	0.00%	4	23.53%
ST company	2015	6	50.00%	3	25.00%	3	25.00%
	2016	8	66.67%	3	25.00%	1	8.33%
	2017	7	58.33%	3	25.00%	2	16.67%
	2018	8	66.67%	2	16.67%	2	16.67%
	2019	9	75.00%	3	25.00%	0	0.00%
Non-ST company	2015	12	41.38%	4	13.79%	13	44.83%
	2016	11	37.93%	9	31.03%	9	31.03%
	2017	10	34.48%	10	34.48%	9	31.03%
	2018	13	44.83%	8	27.59%	8	27.59%
	2019	13	44.83%	6	20.69%	10	34.48%

Table 16. The accuracy rate of prediction of YJFOA-ZSCORE model

Year	2015	2016	2017	2018	2019
The number of companies correctly predicted	32	33	34	35	35
Accurate prediction rate (%)	55.17	56.90	58.62	60.34	60.34

Table 17. The accuracy rate of prediction of YJFOA-ZSCORE model

Year	2015	2016	2017	2018	2019
The number of companies correctly predicted	32	33	34	35	35
Accurate prediction rate (%)	55.17	56.90	58.62	60.34	60.34

The Z-SCORE model of the YJFOA-ZSCORE model optimization results was as follows:

$$Z^{\boldsymbol{\Psi} *} = 1.1364X_1 + 1.4379X_2 + 3.3461X_3 + 0.5968X_4 + 1.0369X_5. \quad \textbf{(25)}$$

Table 14 shows that the YJFOA-ZSCORE model had higher mean, median, and standard error values for Z-scores compared to both the traditional Z-score model and the FOA-ZSCORE model. However, the maximum and minimum Z-score values were similar to those of the traditional Z-score model. The Z-values of YJFOA-ZSCORE model were listed on Table 15.

We observed that the YJFOA-ZSCORE model was not highly sensitive to *ST companies. In 2015, we noticed a shift for certain companies from the Z value range [1.81, 2.675] to a group where the Z values exceeded 2.675. However, the Z values for other years remained consistent with the traditional Z-score model. Regarding *ST companies, the results of the YJFOA-ZSCORE model closely aligned with the traditional Z-score model. For non-*ST companies, the Z value range for some companies expanded in the new model. Nevertheless, the Z values in the YJFOA-ZSCORE model still did not exceed 2.675. This indicates the need for modification of the critical value in the new model. The prediction accuracy rate can be found in Table 16.

The YJFOA-ZSCORE model demonstrated an overall prediction accuracy rate that was similar to the traditional Z-score model, but higher than the FOA-ZSCORE model. However, in order to better align with the actual situation, adjustments were required for the critical value to enhance the accuracy of predictions. The need for modifying the critical value stemmed from the fact that the Z values of the majority of non-*ST companies were concentrated at 1.2 or higher. In contrast, as depicted in Figure 6, the Z values of *ST companies were lower than 1.2. Through multiple experiments based on the Z-value distribution of our sample, we discovered that revising the critical value from 2.675 to 1.2 led to a significant improvement in the prediction accuracy rate for the overall model. The results can be found in Table 17.

Following the adjustment of the critical value, the prediction accuracy rate experienced an increase of 1.72%, 5.17%, 12.07%, and 12.07% from 2016 to 2019.

4.5 Discussion

In this section, we conducted a comparison of all models based on prediction accuracy and RMSE. To begin with, we examined the accuracy rate of prediction. In the case of the traditional Z-score model, there exists a distinct boundary at 2.675 between *ST and non-*ST companies. The group prediction accuracy of our sample in the traditional Z-score model is presented in Table 18.

Table 18. Accurate rate of prediction of the traditional Z-score model

Company category	Year	Number	Accurate rate
ST companies (including *ST)	2015	21	72.41%
	2016	24	82.76%
	2017	25	86.21%
	2018	27	93.10%
	2019	25	86.21%
Non-ST companies	2015	13	44.83%
	2016	9	31.03%
	2017	9	31.03%
	2018	8	27.59%
	2019	10	34.48%

Based on the information provided in Table 16, we can deduce that the accuracy rate of prediction for *ST companies in the traditional Z-score model was approximately 85%. However, for non-*ST companies, the accuracy rate was only around 30%. This indicates that the traditional Z-score model exhibited limited sensitivity towards non-*ST listed companies in the Yangtze River Delta region. On the other hand, the FOA-ZSCORE model made adjustments to its coefficients using real samples, and the corresponding accuracy rate of prediction can be found in Table 19.

Table 19. Accurate rate of prediction: FOA-ZSCORE model

Company category	Year	Number	Accurate rate
ST company (including *ST)	2015	22	75.86%
	2016	24	82.76%
	2017	25	86.21%
	2018	27	93.10%
	2019	25	86.21%
Non-ST company	2015	9	31.03%
	2016	7	24.14%
	2017	8	27.59%
	2018	8	27.59%
	2019	7	24.14%

By examining Table 17, we can observe that the accuracy rate of prediction for *ST companies in the FOA-ZSCORE model closely resembled that of the traditional Z-score model. However, there was a noticeable decline of approximately 10% in the accuracy rate of prediction for the non-*ST companies' group. Consequently, this model proved to be unsuitable for forecasting non-*ST companies.

Furthermore, the study also evaluated the Z-score model optimized through the PSO algorithm, and the corresponding prediction accuracy can be found in Table 20.

Table 20. Accurate rate of prediction: PSO-ZSCORE model

Company category	Year	Number	Accurate rate
ST company (including *ST)	2015	13	44.83%
	2016	13	44.83%
	2017	16	55.17%
	2018	27	93.10%
	2019	25	86.21%
Non-ST company	2015	13	44.83%
	2016	9	31.03%
	2017	9	31.03%
	2018	8	27.59%
	2019	10	34.48%

Based on the data presented in Table 20, it is evident that the PSO-ZSCORE model did not yield satisfactory results for non-*ST companies. Even for *ST and *ST companies, the model only demonstrated higher prediction accuracy for the data from 2018 and 2019.

To achieve more satisfactory results, we developed the YJFOA model. The accuracy rate of prediction for the YJFOA-ZSCORE model can be found in Table 21.

Table 21. Accurate rate of prediction: YJFOA-ZSCORE model

Company category	Year	Number	Accurate rate
ST company (including *ST)	2015	19	65.52%
	2016	24	82.76%
	2017	25	86.21%
	2018	27	93.10%
	2019	25	86.21%
Non-ST company	2015	13	44.83%
	2016	9	31.03%
	2017	9	31.03%
	2018	8	27.59%
	2019	10	34.48%

From Table 21, we can observe that the accuracy rate of prediction for the overall sample, the *ST companies group, and the non-*ST companies group in the YJFOA-ZSCORE model closely resembled that of the traditional Z-score model. However, in the non-*ST companies group, the YJFOA-ZSCORE model exhibited a higher accuracy rate of prediction compared to the FOA-ZSCORE model.

Considering the accuracy rate of prediction, the YJFOA-ZSCORE model emerges as the preferable choice among the various models due to its superior overall accuracy rate and group-specific accuracy rates. Additionally, we can conclude that the accuracy rate of prediction increased from 2015 to 2018. After evaluating the prediction results of the four models, we found that the PSO-ZSCORE model did not perform satisfactorily, leading us to exclude it from consideration. We focused solely on the FOA-ZSCORE and YJFOA-ZSCORE models.

Next, we compared the RMSE of the FOA-ZSCORE and YJFOA-ZSCORE models. Figure 7 illustrates the comparison graph of RMSE over 100 iterations for these two models.

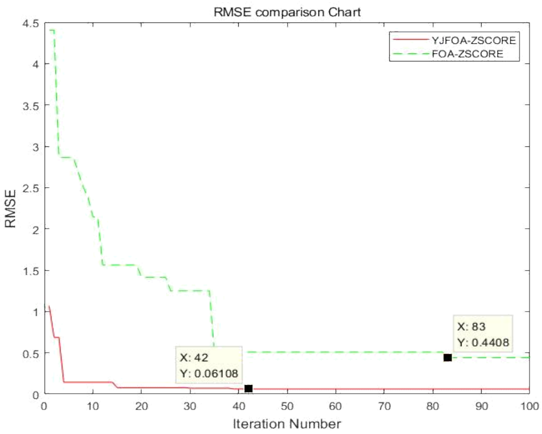

Figure 7. RMSE comparison in 100 iterations

Based on Figure 7, it is evident that the YJFOA-ZSCORE model achieved convergence in the 42nd iteration, with an RMSE value of 0.06108. On the other hand, the FOA-ZSCORE model only converged to 0.4408 in the 83rd iteration, indicating that the YJFOA-ZSCORE model exhibited better performance in terms of convergence. Specifically, the RMSE value of the YJFOA-ZSCORE model remained at 0.06 during the 42nd iteration, demonstrating faster convergence compared to the FOA-ZSCORE model. From these findings, we can conclude that our YJFOA-ZSCORE model possesses advantages in evaluating the Z-score model.

To enhance the prediction accuracy, we made modifications to the critical value of the Z-value, setting it at 1.2. Table 22 provides the Z-value distribution table using this new critical value.:

Table 22. Z value distribution table (modified critical value 1.2)

Type of enterprise		Z<1.2		Z>1.2	
	Year	Number	Percentage	Number	Percentage
ST Company (Including *ST company)	2015	7	24.14%	22	75.86%
	2016	9	31.03%	20	68.97%
	2017	12	41.38%	17	58.62%
	2018	18	62.07%	11	37.93%
	2019	19	65.52%	10	34.48%
Non-ST company	2015	4	13.79%	25	86.21%
	2016	4	13.79%	25	86.21%
	2017	4	13.79%	25	86.21%
	2018	5	17.24%	24	82.76%
	2019	6	20.69%	23	79.31%

In conclusion, by modifying the critical value of the Z-value, the YJFOA-ZSCORE model can achieve an accuracy rate of prediction of approximately 80% for non-*ST companies, while the prediction accuracy for *ST companies can reach around 60%. It is evident that adjusting the critical value significantly enhances the prediction accuracy.

5 Conclusion

To address the issue of lower prediction accuracy, this paper introduced the innovative YJFOA-ZSCORE model as an improvement upon the FOA-ZSCORE model. The results yielded the following insights:

(1) In the traditional Z-score model, the overall accuracy rate of prediction was approximately 50%. However, for *ST companies, the accuracy rate of prediction was higher, reaching around 75%. Conversely, the accuracy rate of prediction for non-*ST companies was merely 35%.

(2) In the case of the FOA-ZSCORE model, the accuracy rate of prediction for non-*ST companies experienced a 10% decrease compared to the traditional Z-score model. This suggests that when the algorithm fitted the actual samples, there was a possibility of neglecting non-*ST company samples or being influenced by extreme values from *ST company samples. Consequently, with smaller sample sizes, the accuracy rate of prediction decreased.

(3) The study also employed the PSO algorithm to optimize the Z-score model. However, the prediction accuracy for *ST and *ST companies was lower compared to the FOA-ZSCORE and YJFOA-ZSCORE models.

(4) Regarding the YJFOA-ZSCORE model, the average and median Z-values closely resembled those of the traditional Z-score model, and the accuracy rate of prediction was also comparable. Notably, our model exhibited a significant increase in prediction accuracy compared to the FOA-ZSCORE model. According to Table 23, YJFOA had the higher accurate rate of predictions in average.

Table 23. Comparison of the results of all algorithms

Algorithm	Accurate rate of predictions (%)
FOA-ZSCORE	53.45-55.17
PSO-ZSCORE	50.0-62.4
YJFOA	55.17-60.34

(5) It was observed that the traditional Z-score model had the drawback of a fixed threshold, leading to lower prediction accuracy in our sample. However, adjusting the critical Z-value with the YJFOA algorithm application proved effective in improving the prediction accuracy, providing valuable insights for further analysis.

Overall, the introduction of the YJFOA-ZSCORE model addressed the limitations of existing models and offered improved prediction accuracy, while the adjustment of the critical Z-value contributed to enhanced insights for analysis.

List of Abbreviations

FOA: Fruit Fly Optimization Algorithm

FOA Z-Score: A Z-SCORE Model Using the Fruit Fly Algorithm to obtain the optimized values of Z-Score

PSO: Particle Swarm Optimization

YJFOA: An Improved Fruit Fly Algorithm innovated by the author.

YJFOA-ZSCORE: A Z-SCORE Model Using the YJFOA to obtain the optimized values of Z-Score

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Biographies

Shianghau Wu is currently the association professor of College of Business at Chung Yuan Christian University. His research interest includes data mining applications.

Jie Yu is the graduate school student of applied economics at Macau University of Science and Technology.

Po-Jui Wu is currently the assistant professor at the School of Business at Macau University of Science and Technology