# Enterprise Financial Risk Early Warning System Based on Catastrophe Progression Method

Bo Hou(✉) and Chang-song Ma

Mianyang Teachers' College, Mianyang 621000, China
houbo698@yeah.net

**Abstract.** When acquiring the risk data, the enterprise financial risk early warning system is easily influenced by the noise data, which leads to the early warning error and low warning accuracy. In order to solve this problem, a financial risk early warning system based on catastrophe progression method is designed. S3C2440A microprocessor is used as the core control module in the hardware part. In the software part, the abrupt progression method is used to mine the abnormal running state, calculate the correlation of the financial data of the risk state, and design the risk warning system after setting the residual value of risk warning. Experimental results show that the average response time of the risk early warning system is about 45 ms, and the accuracy is about 94%.

**Keywords:** Catastrophe series method · Corporate finance · Risk warning · Noise data

## 1 Introduction

In recent years, the economic environment of our country has been developing towards globalization. The risk factors in the economic environment are increasing day by day. High returns are corresponding to high risks. In the process of pursuing profit maximization, companies will inevitably face the challenges brought by risks. If they fail to actively respond to financial risks in a scientific and effective manner, they will probably fall into the financial crisis or even eventually go bankrupt [1]. In recent years, more and more companies in the capital market "flash in the pan" caused academic and practical areas of attention, began to explore how to keep the smooth state of the company continue to operate. In fact, the company from normal operation to the final bankruptcy will go through a gradual deterioration process. There are many influencing factors, possibly due to the allocation of resources, financing, cash management and many other factors, and these factors are usually significant in the financial performance. Therefore, the establishment of financial early warning system, the use of early warning indicators to help companies discover the financial risks, predicting the company's business potential problems in order to timely deal with, to prevent financial crisis.


W. Fu et al. (Eds.): ICMTEL 2021, LNICST 387, pp. 157–169, 2021.
https://doi.org/10.1007/978-3-030-82562-1_14

As for the financial early-warning, foreign scholars have been leading the research, in contrast, our country's relevant theoretical discussion and practical application are relatively weak, which leads to the lack of reliable theoretical support and model reference for our country's enterprise financial early-warning practice, often copying directly the research results of foreign earlier period, and cannot well adapt to the status quo of our enterprises [2]. At the same time, the traditional financial early-warning system is basically based on the accrual basis of accounting information, and its ability to reveal the actual operation of enterprises is bound to be restricted by the inherent limitations of accounting itself; in addition, the traditional financial early-warning system usually only focuses on the static analysis of cross-sectional data, cannot be very good to reveal the gradual process of crisis deterioration, and too much emphasis on complex mathematical model construction, which increases the difficulty of implementation of enterprises, and affects the actual application effect of financial early-warning research results. Thus, it is urgent to explore the financial early warning system with reliable information foundation, dynamic monitoring, scientific, practical and applicability. Therefore, this paper proposes a financial risk warning system based on catastrophe progression method. Through the design of hardware to support the operation of the system, in the software part, the abrupt progression method is adopted to mine the abnormal operation state, and the correlation of the financial data of the risk state is calculated. According to the set residual value of the risk warning, the dynamic warning of the risk is realized, the timely warning of the financial crisis is realized, the interference of the noise on the risk warning is solved, and the warning result is more accurate.

## 2 Hardware Design of Enterprise Financial Risk Warning System

### 2.1 Structure Design of Early Warning Platform

The hardware platform of risk warning system can be designed into four modules, which are microprocessor and memory module, reset and power conversion module, peripheral interface module and sensor signal preprocessing module. The peripheral interface module includes serial interface circuit, JTAG interface circuit, USB interface circuit, buzzer alarm interface circuit, sensor signal preprocessing module.

The early-warning platform uses S3C2440A microprocessor as the core control module, and the periphery includes the storage circuit module, voltage and reset module, peripheral interface module, sensor signal preprocessing module and other hardware platform bottom effects. The actual hardware connection is shown in the following Fig. 1:

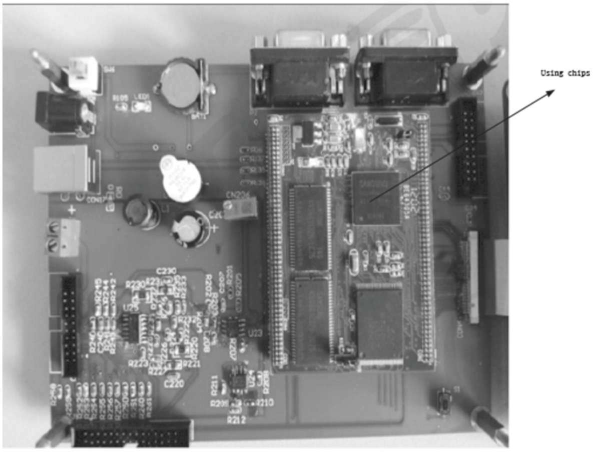


**Fig. 1.** Platform hardware connection diagram

In the above, under the hardware connection mode, S3C2440A microprocessor and memory circuit is located in the hardware system core board, other functional modules are located in the system bottom board, the core board and the bottom board through two rows of $2 \times 50$ pin to fix connection [3]. Serial port, JTAG port and USB port are designed on the hardware backplane, and FPC-40 interface is reserved for LCD screen. The connection with LCD screen can be realized through the switching wire. The hardware backplane of the engineering prototype is encapsulated in a box to meet the requirements of sealing. The interface between the power supply and the sensor is based on the original analog interface, which realizes good compatibility with the machine and reduces the cost of the system transformation [4]. The information processing system adopts S3C2440A microprocessor, which is a 16/32 bit Reduced Instruction Set (RISC) microprocessor of Samsung. S3C2440A uses ARM920T as its core, and adopts 0.13 µm CMOS standard macro cell and memory cell. Its low-power, simple and refined and fully static design can meet the requirements of low power and low cost of embedded system. The results of the integrated functions of the settings chip are as follows (Table 1):

Under the integrated functional control as shown in the table above, a risk early warning platform shall be established and the structure of the risk early warning system shall be as follows Fig. 2:

**Table 1.** Integrated functions of chips

| Serial number | Name | Function |
|---|---|---|
| 1 | Address space | 8 Bank |
| 2 | Simulation debugging | Support for JTAG |
| 3 | Real-time clock RTC | Oral calendar function |
| 4 | Multiplexed input/output port | 130 |
| 5 | External interrupt port | 24 |
| 6 | UART interface | Channel 3 |
| 7 | Multi-host IIC bus interface | Channel 1 |
| 8 | Multiplex ADC | Channel 8 |
| 9 | Watchdog timer | 16 digits |
| 10 | PWM timer | Channel 4 |
| 11 | Internal buffer | 4 KB |
| 12 | LCD private DMA | Channel 1 |

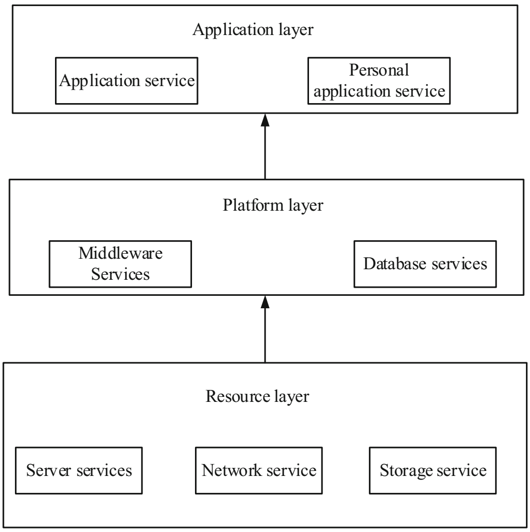


**Fig. 2.** Risk warning platform structure

Under the structure of the early warning platform shown above, the hardware connection circuit structure is designed.

### 2.2 Hardware Connection Circuit

In order to improve the accuracy of A/D conversion, ADC uses a separate power circuit, through the circuit filter and shielding measures to remove burr interference from the PCB board. VSSA is a standalone analog power source with a VDDA range of 2.0–3.6 V. The power supply area is: ADC circuit, reset module circuit, RC oscillator and PLL module analog circuit.

ADC works when VDD is greater than 2.4 V. USB works when VDD is greater than 2.7 V. Provides +1.8 V power for processors, memory, and peripherals in run mode, also known as main mode. In this mode, unused clocks on the APB and AHB buses can be turned off to reduce power dissipation. In stop mode, selectively provide a 1.8 V power supply to supply time-sharing power to certain modules, such as registers and SRAMs, to hold the data in them [5]. This mode is also known as the low power mode of the voltage regulator. In standby mode, the power of the processor circuit can be cut off, that is, the output of the regulator is in the high resistance state. The contents of the register and SRAM are all lost except for the backup circuit. This mode, also known as the off mode, is constructed as shown in the following illustration Fig. 3:

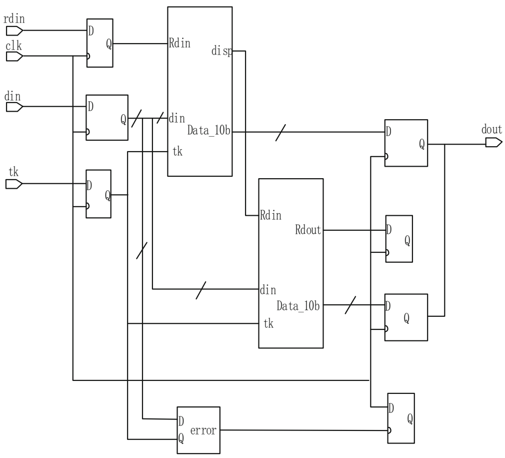


**Fig. 3.** Mode control circuit

In the regulatory circuit structure shown above, all registers are reset except for the reset flag in the clock-controlled CSR and the spare registers. The low level (external reset) of the S1 pin is associated with the time required, the power supply to the processor, the reset value, etc. [6]. In order to make it fully reset, in the +3.3 V power supply working conditions, reset time can be set to about 20 ms. The reset source will eventually act on the S1 pin and maintain a low level during the reset. The reset entry address is 0 × 00000004. The resulting reset circuit structure is shown in the following Fig. 4:

In the reset circuit structure shown above, the power range for setting the VDD is 2.0–3.6 V. A 3.3 V power supply is usually used to power circuits such as I/O interfaces. Built-in voltage regulator for the CPU core to provide the required 1.8 V high-precision

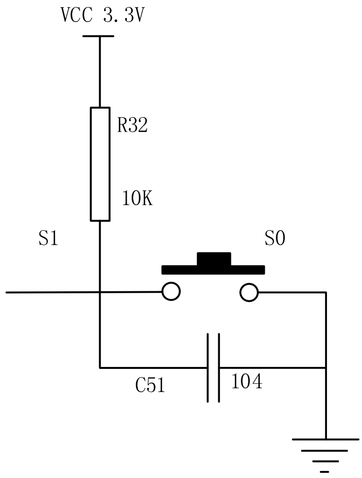


**Fig. 4.** Reset circuit structure

power. After designing the hardware structure of the early warning system, the software part of the early warning system is designed.

# 3 Software Design of Enterprise Financial Risk Warning System

## 3.1 Mining Abnormal Running State by Using Abrupt Progression Method

When diagnosing the running state of a real-time fee control system, the data of abnormal running state of the system shall first be mined and the mining process shown in the following figure shall be followed Fig. 5:

The mining process shown in the figure above, supported by the historical parameters of the operational state of the enterprise financial system, pre-processes the selected data, deletes redundant and inconsistent cleaning data, and unifies the standards for operational state data [7].

The financial system of an enterprise contains a financial system, which defines the relationship between the financial value output and the risk financial value. The expression formula is as follows:

$$P = \frac{1}{2} L_p \left( I^2, R \right) \tag{1}$$

In the above formula, The $P$ represents the output financial data of the enterprise financial system, the $L_p$ represents the data of the risk, the $I$ represents the enterprise profit index, and the $R$ represents the abrupt level parameter. Set the initial value of the cumulative sum in the financial system of the enterprise as 0, and calculate the cumulative sum of each abnormal state data $S$:

$$S = \sum_{k=1}^{i} \left( x_s - \bar{X} \right), i = 1, 2, 3 \ldots F \tag{2}$$

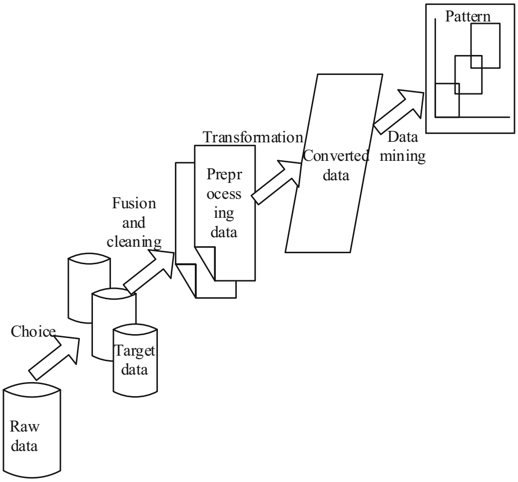


**Fig. 5.** Mining process for financial anomalies

Using the above formula, the extremum of the state data is calculated:

$$\begin{cases} S_{\max} = \max\limits_{k=1,2,\ldots F} S \\ S_{\min} = \min\limits_{k=1,2,\ldots F} S \end{cases} \tag{3}$$

After calculating the extremes in each abnormal data sample, count the number of abnormal data samples between two extremes in the abnormal data sample, The formula defined as $M$, confidence $\lambda$ of the abnormal data at this time is as follows:

$$\lambda = \frac{M}{T} \times 100\% \tag{4}$$

In the above calculation formula, $T$ represents the time series of sliding windows. Set the confidence limit as the warning index [8]. When the confidence limit is exceeded, the financial risk of the enterprise will occur. Based on the abnormal state obtained from the above mining, the relationship between financial data and abnormal state should be established when realizing risk early warning.

### 3.2 Process for Achieving Early Warning

In order to prevent the weak correlation between the above selected state data and the calculated confidence limits [9], the normal operation state of the error risk warning system and the correlation between the calculated state data, the calculation formula is as follows:

$$r_i = \frac{\sum\limits_{j=1}^{k} \left(x_{ij} - \bar{X}\right)\left(y_j - \bar{y}\right)}{\sqrt{\sum\limits_{j=1}^{k} \left(x_{ij} - \bar{X}\right)^2}\sqrt{\sum\limits_{j=1}^{k} \left(y_j - \bar{y}\right)^2}} \tag{5}$$

In the above formula, The $r_i$ represents the correlation coefficient of the $i$ state data, $x_{ij}$ represents the $i$ sample value of the $j$ state data, $y_j$ represents the $j$ sample data in the run state, $\bar{y}$ represents the mean value of the state data in the running state. Define the relevance of $r_i$ values in the above calculation formula as follows:

$$\begin{cases} |r_i| = 0 \\ 0.3 \geq |r_i| > 0 \\ 0.6 \geq |r_i| > 0.3 \\ 0.8 \geq |r_i| > 0.6 \\ 1 \geq |r_i| > 0.8 \\ |r_i| = 1 \end{cases} \tag{6}$$

The quantitative relationship of $r_i$ is defined according to the above formula. When the $r_i$ value is 0, there is no correlation between each state data sample. If the absolute value of the $r_i$ is greater than 0 and less than 0.3, there is no correlation. If the absolute value of the $r_i$ is greater than 0.3 and less than 0.6, there is a low correlation. If the absolute value of the $r_i$ is greater than 0.6 and less than 0.8, the running state data shows a significant correlation. When the absolute value of the $r_i$ is greater than 0.8 and less than 1, there is a high correlation. When the absolute value of the $r_i$ is 1, the running data show complete correlation. According to the above definitions, the relationship between the financial data of the enterprise and the running time of the system is obtained, as shown in the following Fig. 6:

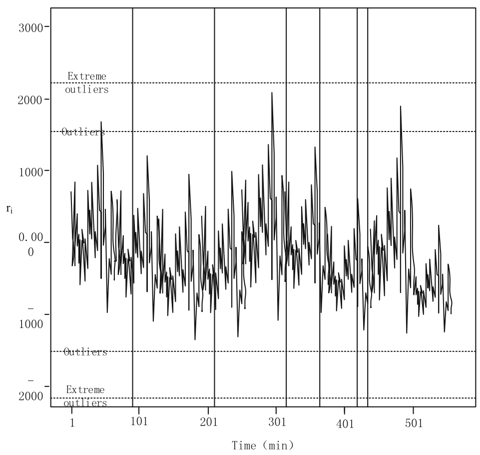


**Fig. 6.** Abnormal values of the running state of a fee- control system

The residual threshold shall be set up for the abnormal value of the operating conditions as shown in the above figure. When the risk occurs to the financial data of an enterprise, the residual threshold appears and drives the collecting central station in the structure of the early warning system to give early warning [10]. Based on the above research and analysis, the final design of the enterprise financial risk warning system based on catastrophe series method.

# 4 System Testing

## 4.1 Build Test Environment

When building a test environment, use a computer with known parameters. The selected computer parameters are shown in the following Table 2:

**Table 2.** Computer parameters used

| Serial number | Name | Parameter |
|---|---|---|
| 1 | Hard disk | 128 GB SSD |
| 2 | Video card | NVIDIA GT 999M |
| 3 | Memory | 8 GB DDR1600 |
| 4 | CPU | Intel core i7-4527QM |
| 5 | Optical drive | DVD-E818A4 119 |

Under the parameters shown in the table above, using Windows CE drivers can be structurally divided into Native Driver and Stream Driver. Local drivers are generally used for built-in, low-level devices, managed by GWES, generally in the system boot is loaded, in the registry also has the corresponding configuration information. The interfaces to implement them are not uniform and the development process is relatively complex. Set the development process for the software as shown below Fig. 7:

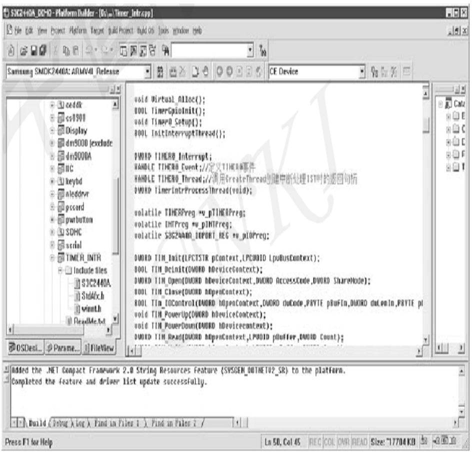

**Fig. 7.** Software development environment

In the software development environment shown in the figure above, after connecting to the CDN server, set up the test environment shown in the Fig. 8:

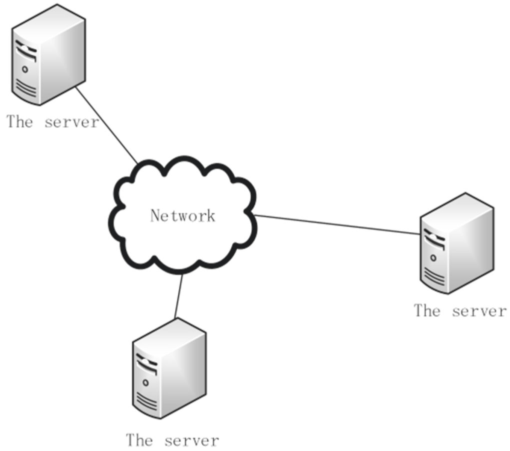


**Fig. 8.** Test environment built

In the above test environment, we use the traditional risk early warning system, [5] risk early warning system and the designed early warning system to compare the performance of the three types of early warning systems.

### 4.2 Analysis of Test Results

Based on the above experimental preparation, the selected financial risks of enterprises shall be transformed into data sources and input into the three risk warning systems. When the corrected dimensions and measurements are correct, the risk warning information at the same level shall be cached, and repeated requests for the same risk warning system shall be made 10 times, and the time from the initiation of the requests to the return of the data of the three risk warning systems shall be recorded. The task request time results of the three risk warning systems are as follows Fig. 9:

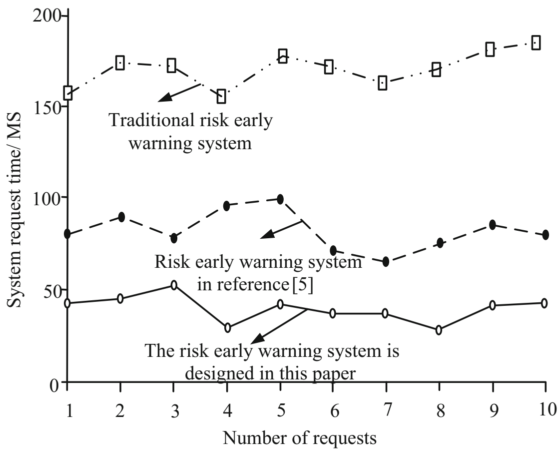


**Fig. 9.** System task request time

Under the same level of enterprise financial risk information, the task request time of the traditional risk early warning system is the longest, and the average task request time is about 220 ms under ten times of requests. The average task request time of the risk early warning system in [5] is about 180 ms and the request time is relatively short. The average task request time of the financial risk early-warning system designed in this paper is about 90 ms, which greatly corrects the shortcomings of the two existing risk early-warning systems. The average task response time of the risk early warning system is about 45 ms. Compared with the existing risk early warning system, the risk early warning system is the fastest to deal with the financial level data.

Under the aforesaid experimental environment, the financial scale of the enterprise for the past three years shall be determined, and the financial investment scale results shall be as follows (Table 3):

**Table 3.** Corporate financial risk data set

| Project name | 2017 | 2018 | 2019 |
|---|---|---|---|
| Monetary capital | 73.36% | 73.36% | 76.17% |
| Inventory | 0.02% | 1.32% | 0.01% |
| Accounts receivable | 2.18% | 13.98% | 1.80% |
| Prepaid and other receivables | 2.18% | 5.46% | 2.32% |
| Due from subsidiaries | 2.21% | 2.46% | 12.60% |
| Investment in other equity instruments | 13.98% | 5.86% | 5.19% |
| Total current assets | 5.84% | 2.18% | 0.73% |
| Fixed assets | 97.59% | 76.4% | 1.91% |
| Long-term equity investments | 1.08% | 0.01% | 25.4% |
| Deferred income tax assets | 0.01% | 76.17% | 1.15% |
| Total non-current assets | 1.32% | 2.41% | 2.32% |

Under the control of the aforesaid risk data, the three risk early warning systems shall deal with the values shown in the above table, correspond to the names of various items in the above table, and make statistics on the accuracy of the early warning of the three risk early warning systems. The accuracy rate is as follows (Table 4):

According to the results of early warning accuracy shown in the above table, three kinds of financial risk early warning systems show different accuracy results. Based on the numerical changes of all the above-mentioned enterprise risk indicators, the accuracy rate of the traditional risk early warning system is the smallest, about 70%, and the accuracy rate of the risk early warning system in the [5] Document is larger, about 85%. The risk early warning system designed in this paper has the greatest accuracy, the accuracy of the value of 94%.

**Table 4.** Accuracy of three risk warning systems

| Project name | Accuracy/% | | |
|---|---|---|---|
| | Traditional risk early warning system | Risk early warning system in literature [5] | Risk warning system designed in this paper |
| Currency funds | 67.6 | 87.8 | 93.1 |
| Inventory | 73.3 | 84.2 | 93.3 |
| Accounts receivable | 68.1 | 87.3 | 93.2 |
| Advances and other receivables | 74.3 | 80.7 | 95.8 |
| Due from subsidiaries | 66.9 | 86.8 | 95.6 |
| Investment in other equity instruments | 65.6 | 83.4 | 94.1 |
| Total current assets | 65.2 | 87.5 | 92.9 |
| Fixed assets | 74.3 | 87.9 | 92.8 |
| Long-term equity investments | 72.5 | 84.5 | 93.9 |
| Deferred income tax assets | 67.4 | 82.8 | 92.5 |
| Total non-current assets | 67.6 | 87.8 | 93.1 |

Based on the above experimental results, the risk early warning system designed in this paper has the shortest task request time and the largest accuracy rate.

## 5 Concluding Remarks

Designing an early-warning system of enterprise financial risk based on catastrophe progression method can provide more scientific, reliable and practical early-warning system for enterprises, improve the ability of management, help operators to monitor the financial status and operation of enterprises in real time, explore and construct an early-warning system of enterprise financial risk which is scientific, reliable and practical, and provide theory and method reference for enterprise financial early-warning management.

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