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應用分類元系統於財務危機預警之研究

Applying Classifier Systems in Financial Distress Prediction Modeling

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中文摘要

財務危機預警對於公司的內部或外部利害關係人，一直是個重要的議題。早期學者多運用區別分析、logistic 迴歸模型、或是 probit 迴歸模型等統計方法建立財務危機預警模型。然而，近年來許多已研究證實，諸如類神經網路(NNs)之人工智慧方法學對於分類問題(ex.預測公司財務危機)有較優異的表現。即使有些學者運用 NNs 預測財務危機得到有效的結果，但由於對資料之敏感性的關係，因而不易建構適當的架構；且在使用模型時，無法提供清楚解釋結果的能力，造成使用之不易。

本研究的主要目的為應用 XCS 分類元系統來建置公司財務危機預警模型。由於 XCSR 模型(一種 XCS 分類元系統的延伸模型)結合了增強式學習(Reinforcement learning)與演化式計算(Evolutionary computation)，因此具備優良的預測能力。且模型中的規則對於預測的結果具可讀性，公司的利害關係人因而較容易了解預測的結果。

經由本研究的實證，結果顯示 XCSR 模型的預測能力將顯著優於比較的 logistic 迴歸模型，以精確度而言，XCSR 模型高達 86.8%，logistic 迴歸模型只有 79.9%。另外，文中亦針對 XCSR 所得之規則，與 logistic 迴歸模型做一討論與比較。

關鍵字：財務危機，財務比率，分類元系統，XCS 分類元系統。

Applying Classifier Systems in Financial Distress Prediction Modeling

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ABSTRACT

The prediction of financial distress is an important and active topic since it is critical to all stakeholders both internal and external to the company. Earlier studies of financial distress prediction used statistical approaches such as multiple discriminant analysis, logistic regression and probit model. Recently, however, several studies have demonstrated that artificial intelligence methodology such as neural networks (NNs), has the superior abilities on classification problems. Even though some of the studies using NNs to the prediction of financial distress have reported its usefulness, there are still several drawbacks in developing and using these models. The sensitivity of financial data would affect building an appropriate model and the learning results could not be read comprehensibly.

The purpose of this paper is to propose XCS classifier systems approach and illustrate how the XCSR model (one model extended from XCS classifier systems) can be applied to financial distress. The exploitation of reinforcement learning and evolutionary computation constitutes a considerably advantage for the XCSR model to provide the superiorly predictive ability. Also, the obtained regularities are a means of easily understanding for the stakeholders of a firm.

The results obtained with the XCSR model showed to be significantly superior to those obtained from the benchmark model (the logistic regression model). The XCSR model has a better accuracy, it is 86.8% accuracy compared to logistic regression model, which only has 79.9% accuracy. Moreover, the extracted regularities were discussed for the increased understanding when comparing to the logistic regression model.

Key words: Financial Distress, Financial Ratio, Classifier Systems, XCS Classifier Systems.

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Chapter 1: *Introduction*

1.1 *Motivation*

The likelihood of financial distress has been an active issue for a long time. It is against the “going concern” assumption and it is critical to many stakeholders both internal and external to the firm. In Taiwan, a series of financial distressed events had started from the second half of 1998, therefore, further shows the importance of this topic.

Many researches have been devoted to the development of financial distress prediction models for providing the solutions to this topic. Earlier studies of financial distress prediction utilized statistical approaches such as multiple discriminant analysis (MDA) (Altman [1], [2]), logit model (Ohlson [3], Shih [4]), and probit model (Zmijewski [5]). However, the restrictive statistical assumption of these conventional statistical methods, such as the required linearity, normality and independence among input variables, is the main problem of implementing them. Recently, several studies have demonstrated that artificial intelligence methodology such as neural networks (NNs), has the superior abilities on classification problems [6]. Even though, since 1990, some of the studies using NNs to the prediction of financial distress have reported its usefulness, there are several drawbacks in developing and using them. The sensitivity of financial data would affect building an appropriate structure [7, 8], and the learning results could not be read comprehensibly [6, 9].

A learning machine paradigm in artificial intelligence, called the “classifier systems”, is a combination of evolutionary computation and reinforcement learning. A set of condition-action rules (i.e., the classifiers) is developed in classifier systems, which is suitable for prediction and classification. Also rules are a useful means to represent knowledge for the applied problems. Classifier systems have been actively developed during the recent years. Many models have been proposed during this developing period. Some of the important features of the systems like its adaptivity and generalization make it successfully when applying to many domains. Therefore, the purpose of this paper is to exploit classifier systems (XCS classifier systems actually, the most promising and applied) and to develop a financial distressed prediction model. Also, to work towards the goal of providing stakeholders of the firm with a more accurate prediction model that consists of rules representing the information about the predicted company.

1.2 *Purpose*

The purpose of this paper is to provide a method that can identify the likelihood of financial distress for the company stakeholders. It can be accomplished by taking quantitative data (financial ratios), processing it into a form that can be used by the XCSR model (one model extended from XCS classifier systems), and predicts financial distress or non-distress. That is, the XCSR model was developed through the use of financial ratios in order to achieve this purpose.

The predicted results of the XCSR model were then compared to a benchmark. A logistic regression model was developed as the benchmark using the same data source. In addition to the comparison of predictive power, the rules obtained from the XCSR model were discussed to the objective of extensive understanding of the financial phenomena to every company. Consequently, to accomplish the purpose, comparisons to the benchmark model and the discussions to the rules provided by the XCSR model were done.

1.3 *Thesis Organization*

This paper was divided into six chapters, and the following gives the detail descriptions of each chapter.

Chapter 1 *Introduction*

--The purpose and motive of conducting this research were described in this chapter.

Chapter 2 *Literature Review*

--Reviewed on past researches on financial distress prediction: the definitions of financial distress, the history of financial distress prediction studies, the frameworks of explanatory variables, and an introduction to classifier systems.

Chapter 3 *XCS Classifier Systems*

--Following section 2.4, this chapter gave more detail descriptions about XCS Classifier Systems, which include the descriptions of terminology and framework.

Chapter 4 *Research Design*

--This chapter gave details about research architecture. The descriptions about the flows of architecture were given.

Chapter 5 *Results and Discussions*

--This chapter presented the summarized results of the XCS model and the logistic regression model. The comparisons about the two models and the rules obtained from the XCS model were discussed.

Chapter 6 *Conclusions*

--The conclusion of result between the two models, and the suggestion of doing further studies were given here.

Figure 1.1 shows the organization of this paper.

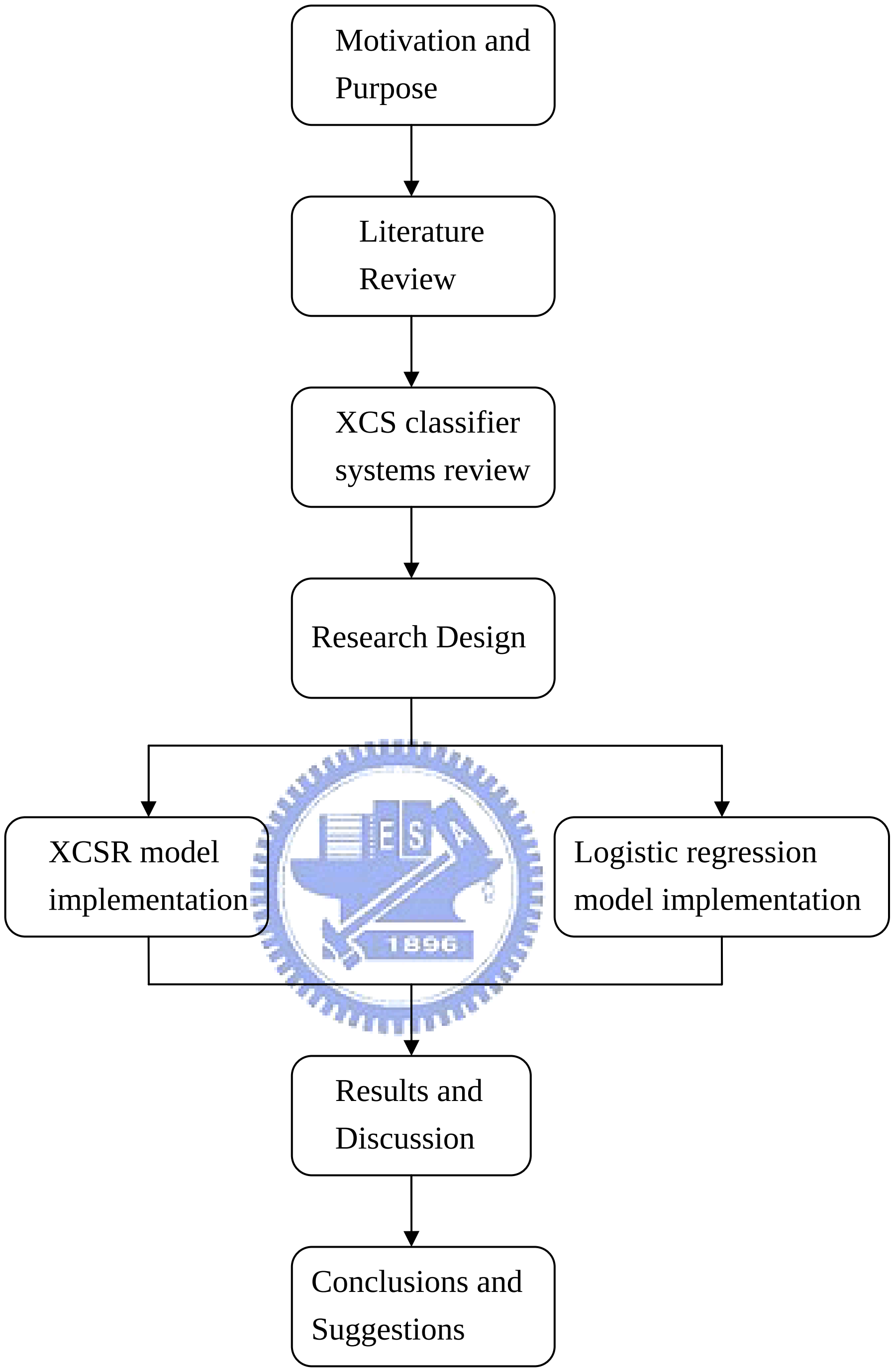

Figure 1.1 Thesis organization

Chapter 2: *Literature Review*

2.1 *Definition of Financial Distress*

A large amount of models have been developed to predict corporate health. Unfortunately, little agreement exists regarding to definite definition of “Financial Distress”. Table 2.1 summarized some of the definitions in priori studies.

Table 2.1 shows that Taiwan differs from the world others on the definition of distressed company. Numerously foreign studies, called bankruptcy prediction, concentrated on those filed for bankruptcy [1, 3, 5, 6, 8]. These companies usually declared relevant bankruptcy legislation in their country (mainly in America). Some other researchers extended their definition to a more general one. The models can distinguish the difference between a healthy firm and an unsound one. But unlike the previous model, this one can also distinguish the different between a healthy firm, and a bankruptcy firm [7, 10, 11, 12, 13, 14]. In other words, the definitions of financial distress are due to the legislation and some perceptions extended by researchers. Therefore, the differences of national condition from other countries result in the distinct definitions of financial distress.

Domestically, the legislations concerning financial distress are: article 49、article 50、and article 50-2 of “Operating Rules of the Taiwan Stock Exchange Corporation”, plus article 211 and article 282 of “Company Law”. The representative events are “listed securities placed under altered-trading-method category, trading been suspended, listing been terminated, declaring bankruptcy, or declaring reorganization”. The number of company declaring bankruptcy in Taiwan [15] was quite few when comparing to other foreign cases. Therefore, they were adopted all together as the definition of financial distress in early studies [16, 17, 18, 19]. However, the latter studies indicated that the financial difficulties should happen in earlier stage [15, 20, 21]. Companies could encounter more or less financial troubles prior to the above-mentioned events. Therefore, recent studies extended relevant events (as in table 2.1) to their operating definitions of financial distress.

To sum up, the differences of national condition among different countries resulted in the distinct definitions of financial distress. Consequently, consider the case in Taiwan, the related legislation and previous studies would be referred as the main definitions of financial distress in this paper.

Table 2.1 Summary of definition of financial distress

Researcher	The definition of financial distress
Altman [1], Ohlson [3], Zmijewski [5] , Shin and Lee [6], Boritz and Kennedy [8]	Companies filed for bankruptcy.
Beaver [10]	Failed companies are defined as meeting one or more of the following conditions: (1). Bankruptcy (2). Bond default (3). An overdrawn bank account (4). Nonpayment of a preferred stock dividend
Altman et al. [7] Varetto [12]	Those underwent one or more of the following condition are defined as distressed companies: (1). Some form of bankruptcy proceeding (2). In temporary receivership (3). In dire straits with regard to their payments to the banks.
Grice and Dugan [11]	Distress companies are defined as meeting one or more of the following conditions: (1). Chapter 11 Bankruptcy (2). Chapter 7 Liquidation (3). Bonds vulnerable to default (4). Low stock rating by S&P
Hopwood [13] Foster and Ward [14]	Companies exhibiting at least one of the following four criteria are considered stressed bankrupt: (1). Negative working capital in the current year (2). A loss from operations, or a retained earnings deficit, or a bottom-line loss in any of the three years prior to bankruptcy (3). Filed for bankruptcy

Table 2.1 *Continued*

Researcher	The definition of financial distress
Hwang [16] Wu [17]	According to article 49 of "Operating Rules of the Taiwan Stock Exchange Corporation", listed company which place their listed security under altered-trading-method category is defined as distressed company.
Cheng [18] Zeng [19]	Listed companies underwent at least one of the following condition are considered distressed. (1). Their listed security is placed under altered-trading-method category. (2). Their listed security is either declared to suspend the trading or to terminate its listing. (3). A firm applied to the court for pronouncement of its bankruptcy or of reorganization.
Shih [4] Chen [15] Kao [20] Liu [22] Jang [21]	Companies exhibiting at least one of the following criteria are considered distressed. (1). They apply to the court for pronouncement of its bankruptcy or of reorganization. (2). Their listed security is placed under altered-trading-method category, or to be deemed a breach of contract. (3). Their listed security is either declared to suspend the trading or to terminate its listing. (4). Their checks were bounced, or they became refused accounts. (5). They apply to someone (often ministry of finance) for mitigating financial difficulties. (6). Their money supply is tight by the bank. (7). Stoppages caused by financial stressed. (8). A bottom-line loss. (9). Audit going-concern opinion. (10). Embezzlement.

2.2 *Overview of Financial Distress Prediction Models*

Since Beaver [10], one of the first researchers to study the prediction of bankruptcy, prediction of corporate failure is a popular topic so far. Many models were structured by different ratios, sample, and methodologies. Some well-known studies will be reviewed next.

Beaver [10] employed a univariate model to examine the predictability of 6 kinds of financial ratios for business failure. He selected a total of 158 samples including 79 failed firms and 79 non-failed firms from 1954 to 1964. Beaver determined that the cash flow to total debt was the best performing ratio. Net income on total assets, the total debt to total assets were the next two best performing ratios.

Beaver's research method in his study deserves some credits. His methods included matched-sample design, addition of new financial ratios, and evaluation accuracy through testing samples, etc. Many researchers later on, had been following his methods. However, the univariate analyses are questionable both theoretically and practically [1]. They ignore the correlation among the financial ratios of several firms resulting in the potential ambiguity inherent in any univariate analysis. Consequently, it is appropriate to further combine several ratios to build a more appropriate predictive model [1, 10].

After Beaver, the first study that used multiple discriminant analysis (MDA) to discriminate the companies into known categories was done by Altman [1]. He improved Beaver's paired sample design upon industry type and firm size to select 33 pairs of manufacturing companies in 1946-1965. A combination of five (selected by a stepwise MDA from an original list of 22) financial ratios were used to build a bankruptcy likelihood score, i.e., Altman's Z-score, as the prediction model. In the short run, it classified quite accurately with a predictive power of 95% one year prior to bankruptcy. However, in the long run, the prediction will not be as accurate as in the short run.

After Altman [1], researchers started to apply discriminant analysis extensively to build predicting models [2, 23, 24]. However, the restrictive statistical assumption of the discriminant analysis, which requires multivariate normality and the equality of covariance matrices, is its main problem [25]. Though violating these assumptions is unimportant if the purpose of the model is to be a discriminating device, nevertheless it results in selection of an inappropriate set of measures [3, 25].

Ohlson [3] addressed this problem and introduced the logistic regression techniques to estimate the probability of bankrupt/non-bankrupt for a company. He utilized nine ratios for his analysis, based on simplicity, and randomly selected 105 bankruptcy and 2058 healthy firms in 1970 – 1976. Though the results were not obviously better than previous ones, he concluded that his methodology was more robust with avoidance of all the problems discussed with respect to MDA [3].

Because the nature of logistic regression analysis required less statistical requirements, many studies followed Ohlson to apply it [4, 13, 14, 16, 19]. Lo [26] compared these two widely used techniques, logit analysis and MDA, through 38 pairs companies in 1975 – 1983. He suggested that logit is a much more robust technique whatever data distributed. However, MDA will be asymptotically efficient while the restrictive assumptions are satisfied. In other words, Lo [26] indicated that the first choice of prediction model would be the logit approach unless the restrictive assumptions are satisfied. On the other hands, Grice and Dugan [11] indicated the cautions for using logit and probit analysis. They evaluated Ohlson [3] and Zmijewski [5] models that utilized logit and probit analysis, respectively. The empirical findings demonstrated that both models were sensitive to time periods. That is, the accuracy of the models in the time periods used to develop them was not consistent with that in the different ones. As a result, they suggested that it is necessary to carefully use the models to avoid erroneous applications of bankruptcy prediction models. That is, it should pay attention to the applied period of the models developed by these two methods. Since the sensitivity to data period would result in incorrect applications.

For many years, artificial intelligence approaches which are less restrictive assumptions, such as inductive learning, Neural Networks (NNs), Genetic Algorithms (GAs), and case-based reasoning (CBR), have been shown that they can be alternative methodologies for classification problems to which conventional statistical methods have been long applied [6]. NNs were the mostly applied techniques for the financial distressed prediction since 1990. The following is a review focused on this approach.

The first study to use NNs for the bankruptcy prediction problem was done by Odom and Sharda [27]. Odam and Sharda built the model with five input variables the same as Altman's financial ratios [1]. They selected a total of 129 research samples including 65 bankruptcy firms and 64 non-bankruptcy firms between 1975 and 1982, where the ratio data were from the financial statement one year prior to bankruptcy. Among these samples, a training set and testing set, consisting of 74 firms (38 bankrupt and 36 non-bankrupt) and 55 firms (27 bankrupt and 28 non-bankrupt), were selected. An MDA was used on the same training set as a comparison. The results indicated the NNs achieved classification accuracy 81.81% of the hold out sample while the MDA only did 74.28%. Tam and Kiang [28] utilized commercial bank failure data to compare the NNs with several methods: ID3 (a decision tree classification algorithm), MDA, logit, and KNN (K-nearest neighbor). The collected bank data included 59 failed and 59 non-failed banks for the period from 1985 to 1987. Among these models, ID3 and KNN were almost worse than the other methods, and NNs presented more accurate and solid results.

Some domestic studies also used NNs for financial distress prediction, which suggested that the NNs model performed more accurate than the other traditional statistic methods [29, 30]. These studies (mentioned above) all showed the usefulness of using NNs to predict financial distress. However, some studies addressed a number of cautions for applying NNs to financial distress prediction. They are discussed below.

Altman et al. [7] applied NNs and MDA to a large database, consisting of over 1000 healthy, vulnerable, and unsound Italian firms from 1982 – 1992, for one-year-ahead prediction. They concluded that NNs were able to accurately predict companies, even in some cases better than MDA. However, the problems with NNs included: illogical behavior patterns in their NNs systems, overfitting in the training stage, and the resulting weights in NNs structure were sensitive to structural changes. All of them negatively impacts predictive accuracy. The overall comparison resulted in no determinative winner, though MDA was slightly better. Bortiz and Kennedy [8] used the NNs models including different training procedures to compare with Altman's model (MDA) and Ohlson's model (Logit). They utilized 6324 (171 bankrupt and 6153 non-bankrupt) companies in 1971 – 1984 with the same ratios chosen by Altman and those chosen by Ohlson. The results showed that the performance of NNs was sensitive to the choice of input variables and that the networks cannot focus on the most important variables through sifting them. Their cautions also indicated the sensitivity of the models to variations in the data. Atiya [9] surveyed numerous financial distress prediction studies on using NNs and presented a NNs model with some novel indicators to improve the accuracy. However, he indicated that one of the existing challenges for the NNs approach is the understanding of the likelihood of financial distress. Statistical methods can show the default probability to assist in recognizing potential distress or non-distress. This is inadequate for the NNs model to show the relevant information.

The above three studies indicated two parts of drawbacks about developing financial distress model using NNs. First, it is difficult to build an appropriate NNs structure. The sensitivity to input variables and structural changes would be the problems. Second, it could not be readily understood by the users when comparing to statistical approaches. The default probability provided by the statistical methods could assist in comprehending the results, but inadequate for NNs. This feature of NNs is therefore referred to as “black-boxes”. Consequently, these two problems should be the cautions while developing financial distress prediction model through NNs.

To summarize the previous studies, the financial distress prediction models have been developed through statistical and artificial intelligence (mainly NNs) methods. Though statistical methodology has applied to develop the prediction model for a long time, its disadvantage is that it required some restrictive statistical assumptions. The NNs models have been demonstrated to predict more accurate than traditional statistical methods, but the drawbacks of developing and using the model are its limitations.

2.3 *Overview of the explanatory variables*

Generally speaking, previous studies utilized one or more financial indicators to the research of predicting financial distress. Mossman et al. [31] mentioned four classes of explanatory variable: financial ratio、cash flow、market-adjusted returns、and standard deviation. They were often used to develop financial distress prediction model. The empirical results indicated that the ratio model presented the most effective in discriminating companies in the year prior to bankruptcy, while the cash flow model offered the most consistent ability to discriminate between bankrupt and non-bankrupt companies in the three years before bankruptcy. In other words, the accounting ratios (financial ratios and cash flow) perform better among these four classes of explanatory variable. Besides, many domestic researchers also used accounting ratios as their indicators to develop models [16, 17, 18, 19]. Therefore, this paper also utilized accounting ratios to develop the financial distress prediction model.

However, although accounting ratios have been successfully implemented to develop models, there exists little agreement regarding to the best accounting ratios to the prediction of financial distress. Table 2.2 summarized some important frameworks of accounting ratios mentioned in Lin [32], which including most of previous studies.

Table 2.2 The frameworks of accounting ratios

Advocate of framework	Description
Leoplod A. Bernstein	Six constructs including 25 ratios
Securities and Futures Commission, Ministry of Finance, R.O.C	Six constructs including 21 ratios
The Bankers Association of the R.O.C.	Five constructs including 29 ratios
Joint Credit Information Center	Seven constructs including 45 ratios

From table 2.2, the framework advocated by Securities and Futures Commission, Ministry of Finance, R.O.C (SFC) is important in domestic studies. According to the laws of "Criteria Governing Information to be Published in Public Offering and Issuance Prospectuses" and "Criteria Governing Information to be Published in Annual Reports of Public Companies", those ratios in the framework should be included in prospectus and annual report. Domestically, the prospectuses and annual reports of companies are the major sources of these ratios. Therefore, the framework announced by SFC is a convinced structure of explanatory variable. Table 2.3 listed those ratios announced by SFC.

Table 2.3 Ratio framework announced by SFC

Category	Accounting Ratio	Category	Accounting Ratio
Financial Structure	Ratio of liabilities to assets	Operating ability	Account receivables' turnover rate
	Ratio of long-term capital to fixed assets		Average days for cash receipts
Debt service ability	Current ratio		Inventory's turnover rate
	Quick Ratio		Payables turnover rate
	Interest coverage folds		Average days for sale of goods
Profitability	Assets return ratio		Fixed assets' turnover rate
	Shareholder's equity return ratio		Total assets' turnover rate
	Net profit ratio	Cash Flow	Cash flow ratio
	Earning per share		Cash flow sufficiency ratio
Leverage	Operational leverage		Cash re-investment rate
	Financial leverage		

Consequently, accounting ratios were widely adopted and successfully implemented in prior studies. Unfortunately, no dominant ratio has emerged. The ratios announced by SFC are an important framework with the essentials of prior studies. Therefore, this framework is the basic structure of explanatory variable in this paper.

2.4 *Overview of Classifier Systems*

Classifier systems are intended as a machine learning paradigm first introduced by John H. Holland in 1975. They combine evolutionary computation and reinforcement learning to develop a set of condition-action rules which show the target regularities from unknown environment that the system has learned from on-line experience [33].

In the early 90s, it appeared that this field was too complex to be studied. Few successful applications had been published. Recently, however, new models have been developed and applied to new domains which resuscitated this area a lot.

Two important characteristics of classifier systems, its adaptivity, and generalization, are important in many application domains such as Computational Economics, Knowledge Discovery, and Data Mining [33]. The adaptivity of classifier systems enables classifier systems to be capable of on-line learning in rapidly changing situations. Generalization is an intriguing and principal feature among them since it makes the system apply what it has learned to previously unobserved situations.

Many applications of classifier systems have been presented [34]. There are three main applied areas consisting of these domains: autonomous robotics, knowledge discovery, and computational economics. In addition to these three areas, there are still other interesting applications. It refers to [34] for more details.

In the past, classifier systems, also called learning classifier systems (LCS), just represented Holland's LCS and most studies focused on the problems that the original model had. Recently, many different models have been proposed with Holland's structure as the main building component. LCS is then identified as the paradigm introduced by Holland. Among these models, Wilson's XCS, Stolzmann's ACS, and Holmes' EpiCS appear particularly promising in the recent years [33]. Since XCS is the most studied and applied in recent years, this paper would then focus on it.

Started in 1987, Wilson modified Holland's ideas to develop a new but simpler LCS. In these years, Wilson's research experienced some important models (NEWBOOLE, ZCS [35]) which eventually evolved to XCS. Though XCS retains the whole main structure of Holland's model, it introduces some essential modifications to the previous architecture, which results in the most promising and the most important breakthrough in LCS research [33]. Regarding to much more description about XCS, it is given in chapter three.

Chapter 3: *XCS Classifier Systems*

3.1 *Overview of XCS*

XCS classifier systems are a learning machine basically, with a mechanism of reinforcement learning. Figure 3.1 shows the learning structure of XCS.

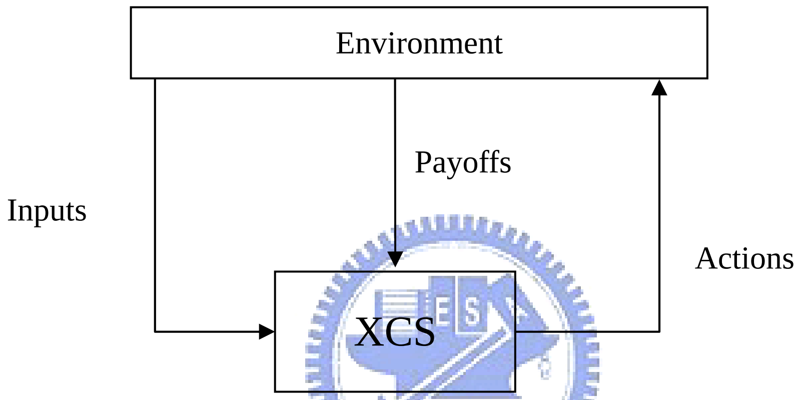

Figure 3.1 The learning structure of XCS [36]

The system learns to get the maximum of reinforcement, the payoffs returned from the environment in figure 3.1. This is the structure of reinforcement learning to act that the adaptability of XCS is improved with time, by means of interaction with the environment.

The learning process is continuing all the time, as XCS goes along. The goal of this on-line learning is to capture regularities (i.e., rules) from the environment. It represents that those situations that map to equivalent consequences are identified and classified together to be represented by internal structure. It takes the advantages of avoiding an extra demand on storage of the raw environmental data. It is an ability to be toward generalization, which is a natural tendency of XCS [33, 37].

In short, XCS is a learning machine which keeps learning ongoing. In the process of learning, regularities hided from environment are caught by XCS. In other words, it attempts to achieve the direction of generalizing inputs from the environment.

3.2 *Terminology and Notation*

3.2.1 *A classifier in XCS*

The regularities contained in XCS are called *classifiers*, which mean knowledge to XCS. They are in the form of condition-action rules defined as follows:

<Classifier> ::= <Condition> : <Action> => <Payoff prediction>

There are a condition part, an action part, and a payoff prediction parameter in a classifier. It represents that if the input from environment is fitted in with the condition of a classifier and the action of it is executed by XCS, then an amount of payoff will be expected. The payoff prediction p is the estimation to a classifier's receivable payoff when condition is matched and action is taken by the system.

In order to reduce the complexity of expressing environment, an input is represented as a string of binary value {0, 1}. Accordingly, the syntax of condition is a string from {0, 1, #}. More than one input can be matched by a condition if it contains #'s [37, 38]. It is explaining as generalization, an important, indeed vital ability for XCS to show regularities of environment compactly [39].

The action chosen by XCS is a discrete value represented as a string. For example, some problems have to be taken as a yes-no decision, then the action of a classifier will therefore be

1 or 0. It is the same as the problem of this paper, to determine a corporation is distress or not. Some classifier examples are showed in Table 3.1.

Table 3.1 Three classifier examples

Classifier_i	Condition					Action	Payoff prediction
	Var.1	Var.2	Var.3	Var.4	Var.5		
Classifier_1	0	0	1	#	#	0	150
Classifier_2	#	1	#	1	0	0	200
Classifier_3	#	0	0	1	#	1	200

Notes: (1) In this example, there are five variables in the condition of a classifier. (2) E.g. if the classifier_1 is satisfied with an input string begins with 001, and action 0 is taken, then a payoff of 150 units will be expected.

It is a limitation to use only two values, 1 and 0 (plus #), to represent each individual variable (bit) of the condition [37]. In many environments, the possible value of the variables of interest is continuous, or is perhaps more than two. Obviously, if there exists continuous variables in environment, then the regularities can only accurately caught by chance. Since it is only in fortuitous cases to set the right thresholds to fit the {1, 0, #} coding.

Wilson [40] brought up a new version of XCS, XCSR (XCS taking real inputs), as a solution to the problem. The traditional syntax of the classifier condition, a string from {1, 0, #}, had been changed to a concatenation of "interval predicates", $\text{int}_i = (c_i, s_i)$, where c_i and s_i are real values [40]. A real input χ, each variable χ_i of the input is a real value, would be matched by the condition if and only if $c_i - s_i \leqq \chi_i < c_i + s_i$ for all χ_i. Hence c_i can be regarded as a center value of int_i and s_i as a "spread" or delta value relative to c_i in int_i. In [40], all χ_i are restricted to the range (0.0, 1.0). It implies that the "don't care" symbol, #, can be replaced as: $\forall \text{int}_i, s.t.\ \text{ci} - \text{si} \approx 0.0 \text{ and } \text{ci} + \text{si} \approx 1.0$. Wilson [40] mentioned that if the data ranges in a real problem are known in advance, such scaling implies no loss of generality. Some examples are showed in table 3.2.

Table 3.2 Three examples of classifiers taking real values

$Classifier_i$	Condition					Action	Payoff prediction
	Var.1	Var.2	Var.3	Var.4	Var.5		
$Classifier_1$	(0.35,0.12)	(0.5,0.5)	(0.76,0.08)	(0.14,0.06)	(0.5,0.5)	0	150
$Classifier_2$	(0.5,0.5)	(0.4,0.13)	(0.68,0.09)	(0.2,0.04)	(0.68,0.14)	0	200
$Classifier_3$	(0.76,0.16)	(0.36,0.12)	(0.5,0.5)	(0.5,0.5)	(0.72,0.08)	1	200

In this paper, all of the used financial ratios are real values. In order to avoid the drawback of the traditional condition encoding and preserve much more information, the model adopted in this paper is XCSR. The following description will focus on XCSR, which just differs from XCS slightly[1].

Besides, there are still another two principal parameters in a classifier: (1) *prediction error* ε, an average of estimation about the error in the payoff prediction parameter with respect to actual payoffs received; and (2) *fitness F*, an inverse function of the prediction error. It made a difference between XCS's definition of fitness and that of traditional classifier systems. The reliability of a classifier in XCS, fitness, is based on the prediction error which is a measure of the accuracy of a classifier's payoff prediction, rather than originally the prediction itself. Moreover, a niche, instead of a panmictic, genetic algorithm is blended. Consequently, it brings on a strong tendency to evolve classifiers into not only accurate but maximally general ones [39].

[1] The differences between XCSR and XCS are only input interface, mutation operator, and covering [40]. Covering takes place while no existing classifier matches the input. The detail description gives in section 3.3.1.

3.2.2 *The different sets*

There are three major sets in XCSR, the same as in XCS, introduced as follows.

- All classifiers contained in XCSR are in the population [P].
- The match set [M] is derived from the current [P]. Those that match the current input from the environment are included in [M].
- The action set [A] is derived from the current [M]. All classifiers of [M] that advocate the taken action are included in [A].

3.3 *The framework of XCSR*

Two kinds of work, single- and multiple-step tasks, can be solved in the frame of XCS. However, to take the problem of this paper into consideration, it is appropriate to apply XCSR for single-step tasks in which an input is detected, an action is taken, and then some payoffs are received form the environment [40].

XCSR comprises three major components in its frame: *performance component, reinforcement component, discovery component* (fig. 3.1). They are separated to give an individual description as follows.

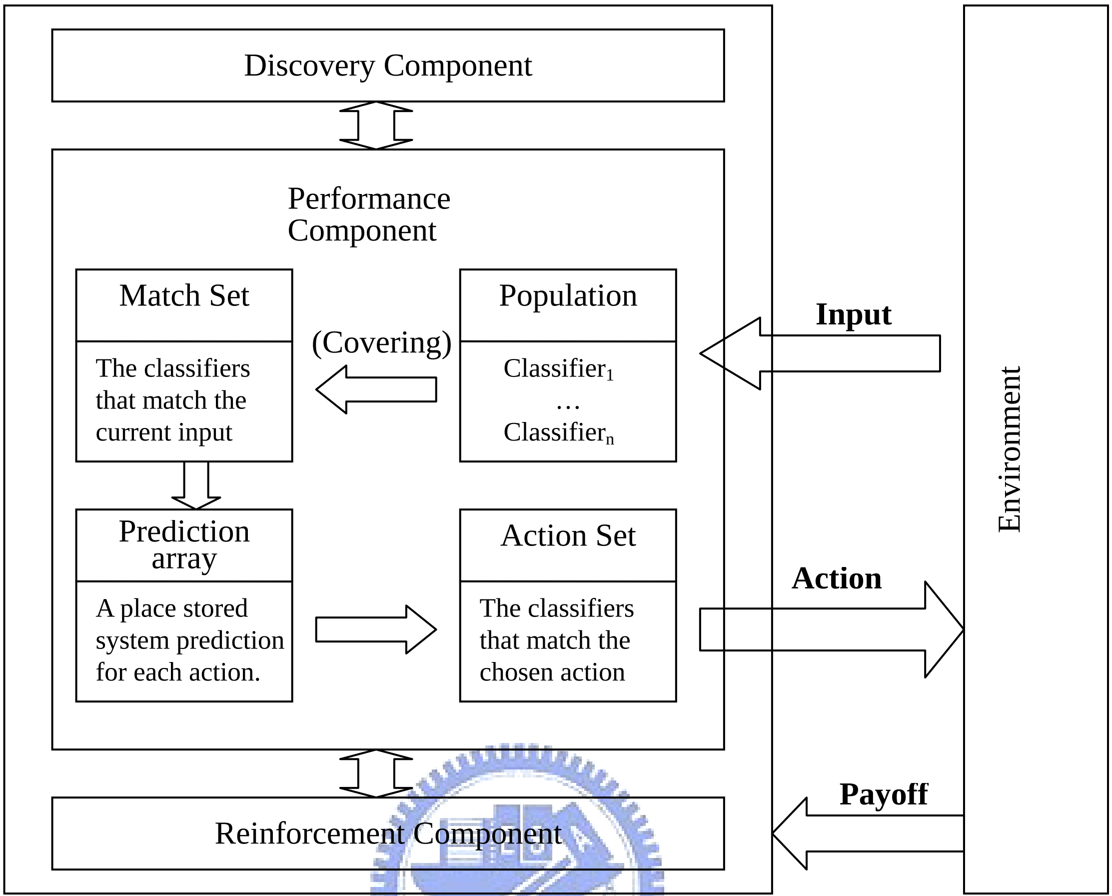

Figure 3.1 The framework of XCS [3]

3.3.1 *Performance component*

According to figure 3.1, it is convenient to divide the description of this component into three parts:

1. Upon appearance of an input, a match set [M] is formed from the current [P]. Covering occurs if the match set [M] is empty. In this situation, the system creates new classifiers which condition matches the input χ for each possible action. In XCSR, the new condition has components int_i with two possible cases. One is "don't care", and the other is $c_i = \chi_i$ and $s_i = rand(s_0)$, where s_0 is a constant such as 0.1 and rand chooses a value uniform randomly from $[0, s_0)$ [40].

2. For every action i presented in [M], the *system prediction* P_i, a fitness-weighted average of the payoff prediction p_j of each classifier C_j in [M], is calculated for each action i.

   P_i is defined as: $P_i = \dfrac{\sum_j F_j p_j}{\sum_j F_j}, \forall i$.

3. An action should be selected in the *prediction array* where each P_i is placed. The criterion to select an action is according to an explore/exploit regime. This regime is a combination of pure exploration (with probability 0.5 [36]) – deciding the action randomly – and pure exploitation – deciding the best one (the largest P_i). The purpose of this action selection method is to take consideration on making best use of what is learned (exploitation) and also on exploring the solution spaces (exploration).

4. While an action is selected in step 3, an action set [A] is formed derived from [M]. All classifiers advocating the chosen action are included. Finally, that action is sent and an amount of payoff is rewarded immediately by the environment.

3.3.2 *Reinforcement component*

The function of this component is to update the p , ε , and F parameters of each classifier in [A]. Hence this component acts on [A] in figure 3.1. The reward R returned by the environment is used to update these three parameters in the order: p , ε , and F. The standard Widrow-Hoff delta rule [41] with learning rate β ($0 < \beta \leqq 1$) is used for updating these three parameters. However, it is activated only after the number of a classifier has been adjusted *exp* is more than or equal to $1/\beta$. This two-state update approach was called “MAM” (“moyenne adaptive modifiée”), introduced in [42]. It makes the early updating procedure quickly to move toward their “true” value, and avoids the system sensitive to beginning, probably arbitrary, setting of the parameters. The following description is given in turn.

1. The p of each classifier in [A] is updated as follows:

   for each classifier C_j in [A], $p_j \leftarrow p_j + \beta(R - p_j)$, if *exp* of C_j > $1/\beta$;

   otherwise, $p_j \leftarrow p_j + (R - p_j)/exp$. (3-1)

   (3-1) is a kind of exponential moving average of R, such that a greater weight is distributed to the latest R. This procedure let p be equal to R eventually, which reinforces p to predict the payoff exactly.

2. The error updating procedure is the same as the payoff prediction update, but not reinforce toward R. It is toward the absolute difference $|R - p_j|$ instead, which is a measure of the classifier's current error [36]. The update equation is as follows:

   for each classifier C_j in [A], $\varepsilon_j \leftarrow \varepsilon_j + \beta(|R - p_j| - \varepsilon_j)$, if *exp* of C_j > $1/\beta$;

   otherwise, $p_j \leftarrow p_j + (|R - p_j| - p_j)/exp$. (3-2)

3. Before updating the fitness of each classifier, the accuracy of its payoff predictions is computed first. The accuracy κ_j of each classifier C_j is the basis of its fitness F_j. It is computed as:

   for each classifier C_j in [A], $\kappa_j = 0.1(\varepsilon_j/\varepsilon_0)^{-n}$, if $\varepsilon_j > \varepsilon_0$; otherwise, κ_j=1. (3-3)

   ε_0 is a threshold under which the accuracy of a classifier is set to 1. Next, the relative accuracy of each classifier κ'_j is computed: $\kappa'_j = \dfrac{\kappa_j}{\sum_j \kappa_j}$. It is an important measure to compare the accuracy with other classifiers in [A], instead of with their absolute accuracy. Finally, the fitness F_j is updated by using κ'_j in MAM procedure. It is calculated as follows:

for each classifier C_j in [A], $F_j \leftarrow F_j + \beta(\kappa'_j - F_j)$, if *exp* of C_j > $1/\beta$;

otherwise, $F_j \leftarrow F_j + (\kappa'_j - F_j)/exp$. (3-4)

Consequently, (3-4) shows that the fitness of a classifier is based on its accuracy, relative accuracy actually, as described in section 3.2.1.

3.3.3 *Discovery component*

In addition to reinforcement learning, discovery component also plays an important role in the process of capturing regularities. The goal of this component is to explore better classifiers and to improve existing ones. It is implemented through a genetic algorithm.

Genetic algorithms (GAs) are stochastic search techniques inspired from natural evolution [43, 44]. In a wide range of applications, GAs have been demonstrated that searching in large and complex spaces is effective and robust [44]. Therefore, GAs are regarded as the way of leading rule discovery in XCS [33].

Figure 3.2 shows the flowchart of a genetic algorithm taken place in the XCSR model. The following is an abbreviated description about it. It is refer to [43, 44] for a more complete description of genetic algorithms.

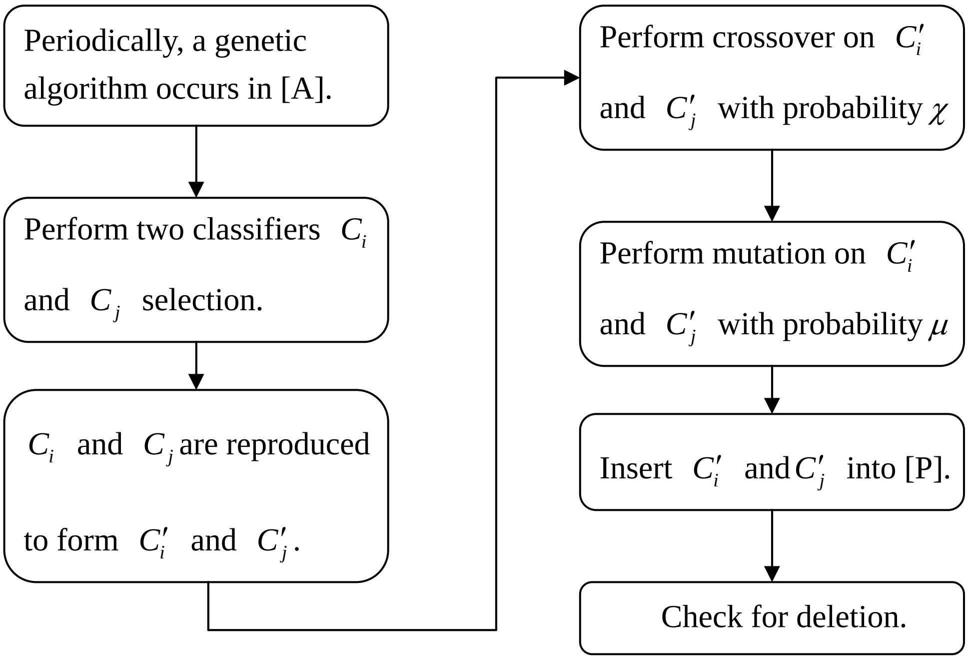

Figure 3.2 Flowchart of GAs in XCSR.

In the beginning, a GA is executed in a certain period. The population of the GA is the current action set [A]. That is, the discovery component acts on [A]. Then, two classifiers C_i and C_j are selected according to the probability proportional to their fitness and copied to form C_i' and C_j'. With a high probability χ, also called crossover rate, C_i' and C_j' are crossed (two-point crossover). Figure 3.3 shows an example.

(0.35, 0.02) (0.5,0.5) | (0.43,0.08) (0.5,0.5) | (0.48,0.15) : 1
(0.5,0.5) (0.38,0.1) | (0.82,0.03) (0.76,0.06) | (0.5,0.5) : 1

⇩

(0.35, 0.02) (0.5,0.5) (0.82,0.03) (0.76,0.06) (0.48,0.15) : 1
(0.5,0.5) (0.38,0.1) (0.43,0.08) (0.5,0.5) (0.5,0.5) : 1

Figure 3.3 An example of crossover.

The crossover points, the positions of vertical line in figure 3.3, are randomly selected. The selected parts of C_i' and C_j' are exchanged with each other to form new ones. The purpose of crossover is to combine two accurate classifiers to yield better ones. In this example, a new classifier is more general than its parents, and the other one is more specific. This situation may not always happen, but it is a tendency toward the balance of generality-specificity [36].

Next, mutation occurs per allele with a very low probability μ (also called mutation rate). It is performed by adding an amount ±rand(m), where m is 0.1 and the sign is chosen uniform randomly. This method was introduced in [40]. The aim of mutation is to introduce innovation to prevent losing some potentially useful genetic material [44].

And then, C_i' and C_j' are inserted into [P]. If the maximum population size N is reached, two classifiers must be deleted in [P]. The probability of deleting a classifier is confirmed by Kovacs [45]. Low-fitness classifiers that have participated in a threshold number of action sets are preferentially selected to be removed.

It is worth to explain the reason why GA is taken place periodically and the necessity of deletion. It is designed with the aim to keep the resources of the system balanced. Balance means that approximately equal numbers of classifier are allocated to each action set (called niche). Some niches may appear more frequently than others in some environment, so that there are different payoff levels in different niches of the environment. To avoid population full of classifiers in high-payoff niches, it is necessary to balance the active classifiers to share the available payoff [38]. Therefore, it is a niche GA, not a panmictic one, to assist XCSR in discovering more accurate and general classifiers.

3.4 *Summary*

XCS classifier systems are a learning machine exploiting reinforcement learning and evolutionary computation (GAs) to capture regularities from the environment. The developed regularities represent the generalization of inputs for that environment. That is, XCS learns some knowledge about the environment.

The accuracy-based feature makes XCS to discover regularities which are not only accurate but maximal general. These regularities are therefore suitable for prediction and classification. To match the format of this paper’s inputs, financial ratios, the representation of condition in a classifier is an interval for real value. This XCSR model is similar to the original XCS model with extending the representation of inputs.

Consequently, because of the accuracy-based characteristic and the regularities extracted from the environment, this paper would utilize the XCSR model to develop the financial distress prediction model for an accurate result.

Chapter 4: *Research Design*

According to the review in previous chapters, several methods were applied to develop the financial distress prediction model but with some drawbacks. XCS classifier systems taking real inputs (XCSR) are a learning machine adequate for prediction described in chapter three. To achieve the purpose of this paper, it therefore implemented the XCSR model with the data from the listed companies in Taiwan. Since logistic regression provides relatively less statistical assumption but more information about the predicted company than NNs, it was then developed with the same data for the comparisons to the XCSR model.

This chapter described the details about the architecture of this paper. It included the selected sample, research limitation, experimental models, and descriptions about the statistical tests.

4.1 *Research Architecture*

The purpose of this paper was to construct XCS classifier systems taking real inputs (XCSR) for the prediction of financial distress and non-distress. The developed XCSR structure was then compared and evaluated against logistic regression model. The architecture of this paper showed in figure 4.1.

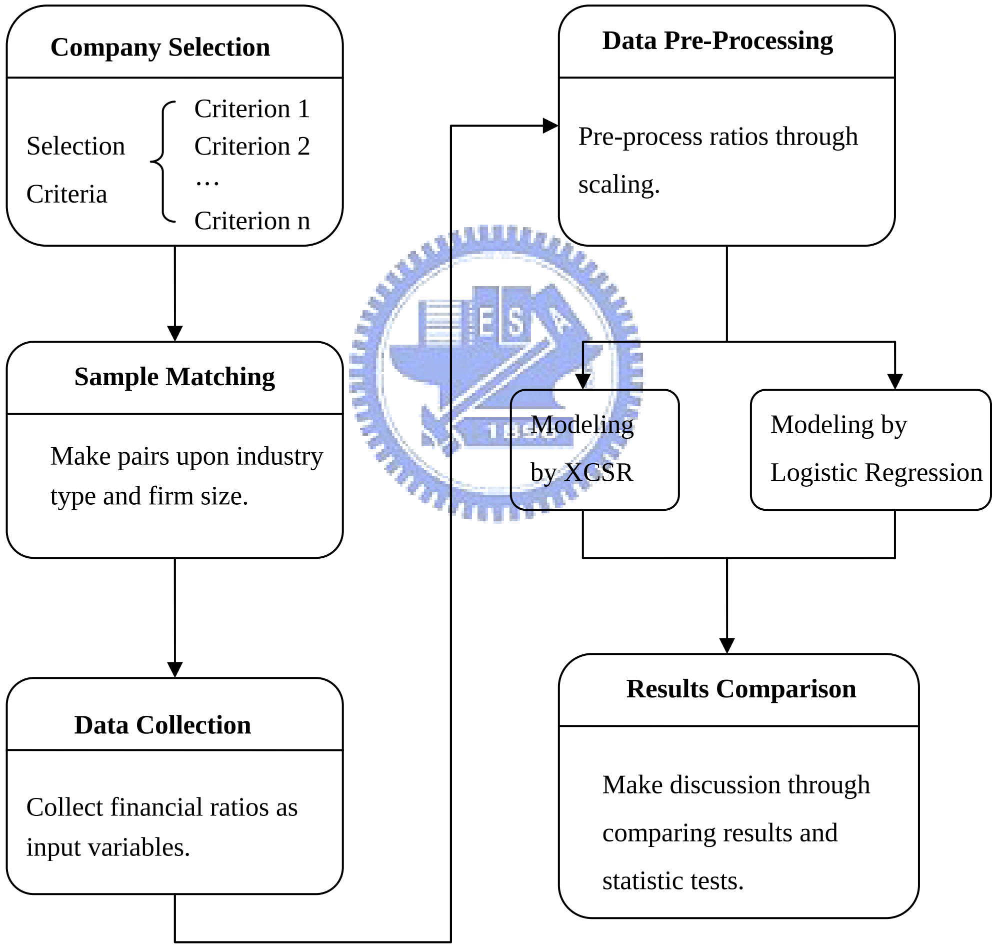

Figure 4.1 Research Architecture

From figure 4.1, this paper utilized historically financial ratios as the inputs of models for the prediction of financial distress and non-distress. Companies were selected according to different criterion which is the operating definition of this paper. Distressed companies were compared with non-distressed ones preceding the time period in which the distressed event happened. Data were collected using equivalent lead times, and then pre-processed for available in the XCSR model.

The method developed for the prediction was a XCSR model. During the training period, the XCSR model captured the regularities between the financial ratios and distress or non-distress. And this paper utilized the identical financial ratios to formulate the logistic regression model. The XCSR model was then compared to conventional logistic regression model for their obtained results. Finally, the results of two models presented to make some discussion and conclusion.

4.2 *Sample Selection*

4.2.1 *Selection Criteria*

On the basis of previous studies and domestic circumstances, distressed companies were defined as meeting at least one of the following criteria:

- A company applied to the court for pronouncement of its bankruptcy or of reorganization.
- Their listed security was placed under altered-trading-method category.
- Their listed security is either declared to suspend the trading or to terminate its listing.
- Their checks were bounced, or they became refused accounts.
- A company applied to someone (often ministry of finance) for mitigating financial difficulties.
- Their money supply is tight by the bank.
- Stoppages caused by financial stressed.

For those selected distressed companies, the corresponding non-distressed ones were then matched under industry type and firm size during the same time. The size of a company was determined by its assets. The determination of a company's industry type was referred to the industrial category announced by Taiwan Institute of Economic Research (TIER). This category used here differs from previous studies. Domestically, prior studies mostly used the industrial category announced by Taiwan Stock Exchange Corporation (TSEC). However, it was quite simpler than the "Standard Industrial Classification System of the Republic of China" published by Directorate-General of Budget, Accounting and Statistics Executive Yuan (DGBAS) in January 2001. In order to avoid mismatching, this paper used the industrial category announced by TIER which provided more detailed industrial classification following DGBAS's version.

4.2.2 *Experimental Data*

1. *Research Scope*

This paper used 1999 – 2003 data from Taiwanese listed companies, as reported in TEJ database. The selection and paired criteria were those described in section 4.2.1. On the other hands, it is similar to prior studies that financial institutions are excluded, with the reason that their ratios and cash flows existed substantial differences from those of other types of firms.

The final sample, approximately with proportion of 1 distressed to 2 non-distressed firms, included 182 firms (65 distressed and 117 non-distressed). The sample distribution for the distressed and non-distressed firms is summarized in table 4.1.

Table 4.1 Sample distribution by year

Group	1999	2000	2001	2002	2003	Total
Distressed	16	18	12	12	7	65
Non-distressed	29	33	21	23	11	117

The distributions for the sample were partitioned into a training set and a testing set. The training data is used with the aim to estimate coefficients in logistic regression model and to capture regularities in XCSR model, and then the testing data is used to measure adaptability of both models. The training sample contained 1999 – 2001 data with 129 companies (46 distressed and 83 non-distressed), and the testing sample consisted of 2002 – 2003 data with 53 companies (19 distressed and 34 non-distressed).

2. *Data Sources*

The distressed events of companies were obtained from *TSEC monthly review* No.442 to No.501 and Securities and Futures Institute (SFI) Online Database. And the sample financial data was collected from Taiwan Economic Journal (TEJ) Database. If there were still inadequate from the above source, plus Market Observation Post System、seasonal reports、and prospectus as supplements.

4.2.3 *Research variables*

Mostly, the preceding researchers used annual financial statement to calculate the ratios. However, the information disclosed in annual reports was much latter than that in seasonal financial statements. Besides, SFC requested the listed companies should publish their financial statements every season. Therefore, this paper used the seasonal financial ratios for more information, instead of yearly ones. Before introducing the selected ratios in this paper, a timing issue of selecting ratio period mentioned by Ohlson [3] should be discussed.

The time of announcing financial statements was necessary to pay attention to. In Taiwan, the time points of publishing financial statement showed in figure 4.2.

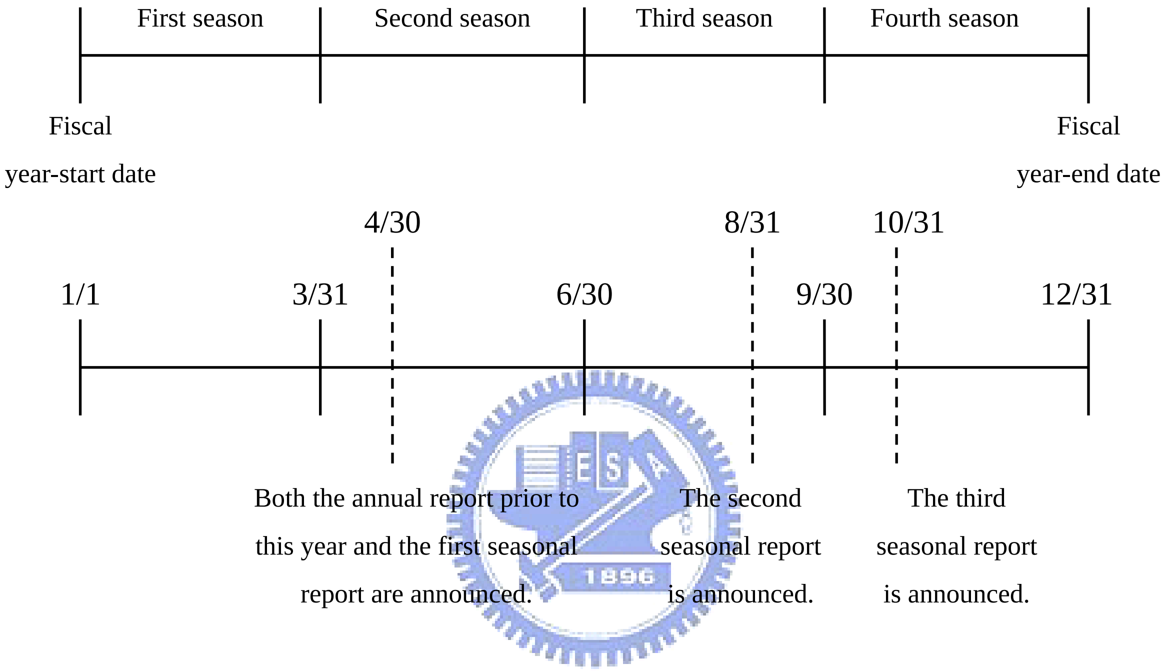

Figure 4.2 the time point of announcing financial statement [46]

Previous studies seemed implicitly to consider the timing issue. Studies using annual reports were to give an example. From figure 4.2, the annual data is reported next March. It seemed that these studies, but by no means all, presume that a financial statement is available at the fiscal year-end date. However, it is possible that a distressed event took place at the time point after the fiscal year date, but prior to announcing the financial statements. This was the problem Ohlson [3] addressed which may lead to “back-casting” for many of the distressed companies.

In order to avoid this problem, the selected period of every distressed firm was designed as figure 4.3.

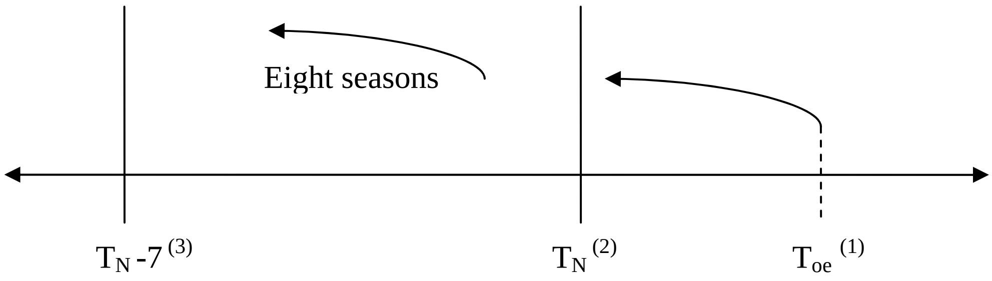

Figure 4.3 Time point selection

Notes:

(1) T_{oe} represents the occurrence of financial-distressed event.

(2) T_N represents the nearest financial statement announcements prior to T_{oe}.

(3) T_N -7 represents the time point eight seasons prior to T_N.

According to figure 4.2, while a distressed event of a company took place at the time T_{oe}, the nearest time point of announcing financial statements prior to T_{oe} , T_N , was then determined. For example, if a distressed event of a company arose at the middle of July (T_{oe}), then T_N should be April which indicated the second seasonal report instead of the third one. After determining T_N, the corresponding seasonal report was also determined. Then the data period was between T_N and the time point T_N -7 seven seasons priori to T_N. In other words, this paper used the financial ratios of each distressed company calculated from T_N -7 to T_N (i.e., total 8 seasons) and used the same period for the paired non-distressed companies.

According to section 2.3, the framework announced by SFC was the basic structure for this paper's input variables. In addition to this, the selected ratios were also considered on the basis of their performance in prior studies. In other words, this paper has taken practical and empirical considerations on choosing explanatory variables. Table 4.2 listed these selected ratios in this paper.

Table 4.2 Selected variables [47]

Category	Variable	Formula	Description
Liquidity Construct	Current Ratio	$\frac{current\ Assets}{Current\ Liabilities}$	• This ratio evaluates an enterprise’s short-term debt-paying ability and overall liquidity position. • The higher this ratio, the less probability a company becomes financially distressed.
	Quick Ratio	$\frac{Quick\ Assets}{Current\ Liabilities}$ Quick assets = current assets - inventory	• In addition to current ratio, it is prefer to examine a more immediate liquidity position at times. That is, quick ratio. • The usual guideline of this ratio is larger than 1.00.
	Working Capital to Total Assets Ratio	$\frac{Working\ Capital}{Total\ Assets}$	• This ratio measure a company’s liquidity relative to the total capitalization. A shrink of this ratio often represents an operating loss of the firm.

Table 4.2 *Continued*

Category	Variable	Formula	Description
Capital Structure Construct	Times Interest Earned	$\frac{\textit{After-tax Net}\text{ Income, plus Interest Expense, and Income Tax Expense}}{\textit{Interest Expense}}$	• This ratio evaluates a company's ability to pay the interest expense by net income. That is, the level of meeting its interest obligations.
	Debt Ratio	$\frac{\text{Total Liabilites}}{\text{Total Assets}}$	• This ratio measures how well creditors are protected in case of insolvency. • The higher this ratio, the worse the company's position.
	Permanent Capital To Fixed Assets Ratio	$\frac{\text{Equity} + \text{long-term debt}}{\text{Fixed Assets}}$	• This ratio determines how well the fitness between capital structure and assets structure.
	Fixed Assets to Total Assets Ratio	$\frac{\text{Fixed Assets}}{\text{Total Assets}}$	• This ratio determines how well the fitness between fixed assets and assets structure.
Cash Flow Construct	Cash Flow Ratio	$\frac{\text{Cash Flow from operations}}{\text{Current Liabilites}}$	• This ratio evaluates the payback ability to meet short-term debt by generating resources.

Table 4.2 *Continued*

Category	Variable	Formula	Description
Operation Performance Construct	Inventory Turnover	$\frac{\text{Cost of Goods Sold}}{\text{Average Inventory}}$	• This ratio determines the liquidity of the inventory, which helps to understand the managing performance of inventory.
	Accounts Receivable Turnover	$\frac{\text{Net Sales}}{\text{Average Gross Receivables}}$	• This ratio evaluates the liquidity of the receivables, which helps to make decisions about extending sales.
	Total Asset Turnover	$\frac{\text{Net Sales}}{\text{Average Total Assets}}$	• This ratio determines the activity of the total assets and also the ability of the company to generate sales through utilizing the total assets.
	Fixed Asset Turnover	$\frac{\text{Net Sales}}{\text{Average Fixed Assets}}$	• This ratio measures the activity of the fixed assets and the ability of the firm to generate sales through the use of the fixed assets.

Table 4.2 *Continued*

Category	Variable	Formula	Description
Profitability construct	Net Income to Sales Ratio	$\frac{\text{Net Income}}{\text{Net Sales}}$	• This ratio measures the profitability of the company.
	After-Tax Return On Assets	$\frac{\text{After-Tax Net Income}}{\text{Average Total Assets}}$	• This ratio evaluates the ability of the firm to create profits through utilizing its assets.
	After-Tax Return On Equity	$\frac{\text{After-Tax Net Income}}{\text{Average Total Equity}}$	• This ratio measures the firm's ability to generate return to the shareholders.
	Gross Profit Margin	$\frac{\text{Gross Profit}}{\text{Net Sales}}$	• This ratio evaluates the ability of the firm to produce a good or service at a low cost or a high price.
Growth construct	Sales Growth Ratio	$\frac{\text{Net Sales}_t - \text{Net Sales}_{t-1}}{\text{Net Sales}_{t-1}}$	• This ratio measures a firm's degree of growth for the net sales after tax.
	After-Tax Net Income Growth Ratio	$\frac{\text{After Tax Net Income}_t - \text{After Tax Net Income}_{t-1}}{\text{After Tax Net Income}_{t-1}}$	• This ratio measures a firm's degree of growth for the net income after tax.

These ratio data was required to be pre-processed for the usage of XCSR. The pre-processing procedure used the following formula:

$$\chi_{i,j}' = \frac{\chi_{i,j} - \min_j}{\max_j - \min_j}, \forall 1 \le i \le m, 1 \le j \le n \tag{4-1}$$

Where:

$\chi_{i,j}$: The ith record of jth ratio

$\chi_{i,j}'$: The processed value of $\chi_{i,j}$

$\min_j$: The minimum of jth ratio

$\max_j$: The maximum of jth ratio

m: The total number of record in data
n: The total number of financial ratios

(4-1) involved mapping each ratio to a range with minimum and maximum values of 0.0 to 1.0, respectively. For the transformed format, it would suit for the inputs of the XCSR model.

4.3 *Research limitation*

It did not include all the practically influenced variables for the likelihood of financial distress in this paper. Some restrictions of this paper are given as follows:

- Sample limitation: This paper used only listed companies with the reason that their financial data is much more confidence than the unlisted companies. The selected sample is therefore with the restriction on the listed companies.
- Accounting limitation: The financial ratios used in this paper were calculated from the financial statements. There may take place bias among the company's ratios because of

the differently calculated methods under generally accepted accounting principles. It is an unavoidable restriction.

- Data limitation: This paper only used the quantitative data. That is, the financial ratios. For other qualitative variables are not in the considered range.

4.4 *Implementation Models*

4.4.1 *XCSR Model*

This paper implemented Wilson's [40] XCSR model with almost the same structure (see figure 3.1). The input in this paper was the pre-processed financial ratio, and the corresponding taken action was the predicted result. The form of a classifier was similar to that in table 3.2. With regard to every input (a financial ratio) from environment, XCSR will chose the suitable classifiers to take an action (to predict distressed or non-distressed). If it predicts correctly, the environment will reinforce those in action set with positive payoff; otherwise with -100. Finally, the classification accuracy was calculated to compare with that of logistic regression model. For the comparison with fair, those inputs caused the mechanism of covering, not been predicted by XCSR, were excluded in calculating the accuracy.

The major parameters in the XCSR model listed below, additional information about XCSR referred to chapter three.

- N, the maximum size of the population, equals 400.
- β, the learning rate for p, ε, and F, equals 0.4.
- ε_0 and n, used to compute the fitness of a classifier, are 10 and 5.
- θ_{GA}, the threshold to determine whether GA can take place, equals 15.

- χ, the crossover rate, equals 0.8.
- μ, the mutation rate, equals 0.05.
- P#, the probability of using a don't-care in one variable in a classifier when covering, equals 0.8.
- R, the payoff returned by the environment, equals 1000 for the correct action; -100 otherwise.

4.4.2 *Logistic Regression Model*

Previous studies often used logistic regression model with the main reason that it has less statistical assumptions than MDA and linear regression model to deal with dichotomous variables. Additionally, it could handle nonlinear variables and transform the value of the dependent variable into probability which was meaningful to users. Therefore, this paper used logistic regression model as the benchmark compared with XCSR.

The logistic regression gives the equation as follows:

$$y_i^* = \beta_0 + \sum_{j=1}^{n} \beta_j \chi_{i,j} + \mu_i \quad , \qquad y_i = \begin{cases} 1 \text{ if } y_i^* > 0 \\ 0 \text{ otherwise} \end{cases} \tag{4-2}$$

Where:

y_i^*: The estimated (latent) variable

y_i : The observed variable representing whether the i_{th} company is distressed ($y_i = 1$) or not ($y_i = 0$)

$\chi_{i,j}$: The j_{th} financial ratio of the i_{th} company (total j ratios)

β_j : The estimated coefficient of $\chi_{i,j}$ (β_0 is the estimated intercept)

μ_i : The error term

In (4-2), the conditional probability of y_i was then transferred as:

$$\mathrm{P}(y_i = 1 \mid \chi_{i,j}, j = 1 \cdots n) = \mathrm{P}\left[\mu_i \le (\beta_0 + \sum_{j=1}^{n} \beta_j \chi_{i,j})\right]$$

$$= F\left[\beta_0 + \sum_{j=1}^{n} \beta_j \chi_{i,j}\right] = \frac{1}{1 + e^{-(\beta_0 + \sum_{j=1}^{n} \beta_j \chi_{i,j})}} \tag{4-3}$$

In (4-3), the cumulative distribution function of μ_i (function F) is assumed as a logit function. For this reason, these independent variables (financial ratios) could be transformed to an estimated probability fell into a range between 0.0 and 1.0. This paper used a cutoff value equaling 0.5 as a threshold of the prediction. In other words, the model determined a company as distressed while its estimated probability is greater than 0.5, otherwise determined it as non-distressed. Moreover, the stepwise procedure was used to determine the significantly explanatory variables. The criterion for entering and removing variables in the model was a 0.10 and a 0.15 probability level, respectively.

4.5 *Statistical Test Description*

The purpose of using statistical tests is to prove the significance of the predictive results. The tests were done in three parts: classification accuracy test, differences between two models' accuracy test, and tendency test. The descriptions for individual test were given bellow.

1. *Description of Test for Classification Accuracy*

In order to evaluate the accurate level both models achieved, a statistical test introduced by Huberty [48] was used. He proposed a test statistic Z* which follow an approximately normal probability distribution, for assessing the statistical significance of the classification rate is given by

$$Z^* = \frac{(o-e)\sqrt{n}}{\sqrt{e(n-e)}} \tag{4-4}$$

$$e = \frac{1}{n}\sum_{g=1}^{G} {n_g}^2$$

where n_g is the number of observations in group g; n is the total number of observations; e is the expected number of correct classifications due to chance for the total sample; and o is the total number of correct classifications.

If the statistic calculated in (4-4) is significant at the level of 0.05, it therefore suggests that the classification accuracy is significantly greater than due to chance [25, 48].

2. *Description of Test for Differences between Two Models' Accuracy*

For the obtained accuracies from both models, the purpose of this test was to show whether the accuracy for the XCSR model is significantly higher than that for the logistic regression model. The test was designed as the large-sample paired test statistic for the difference between two population means using the testing sample [49]. The null and alternative hypotheses are given:

H_0 : $\mu_D \leqq 0$

H_1 : $\mu_D > 0$

μ_D is the mean of the differences of the accurate rates between two models. The critical value of the z statistic, at a significance level of 0.05, was 1.65. If the null hypothesis was rejected, it showed that the XCSR model is significantly more accurate than the logistic regression model at a significance level of 0.05.

3. *Description of Test for Tendency*

The tendency of the classification accuracy for distressed companies in XCSR was tested to show whether it is upward or downward. It was designed to structure a linear regression model as follows:

$$y = \alpha + \beta\chi \tag{4-5}$$

χ is the time point and y is the corresponding accuracy of distressed companies.

The coefficient of χ in (4-5), that is, β, showed the tendency of accuracy. The XCSR model possessed an uptrend in the prediction of distressed companies with time if β is positive, a downtrend otherwise.

Chapter 5: *Results and Discussions*

In this chapter, the experimental results were presented and discussed. The benchmark model was presented at first in section 5.1. The collinearity problem and predictive results were discussed. After showing the results of the logistic regression model, they were then compared to those of the XCSR model in 5.2. Section 5.3 showed that the differences of predictive accuracy between two models are significant by statistical tests. Tendency of accurate rate for distressed companies in the XCSR model was discussed in 5.4. At last, the regularities in the XCSR model were discussed in 5.5.

5.1 *Logistic Regression Model*

1. *Collinearity Tests*

Prior to develop the logistic regression model, the collinearity among the independent variables should be determined at first. Low levels of collinearity are not generally influential. However, high levels of collinearity could result in the problems of the estimation for the standard errors of coefficients. The Tolerance statistic is a useful indicator to detect the levels of collinearity. According to the rough guidelines stated in Menard [50], a tolerance of less than 0.2 could be a caution for concern. A serious collinearity problem appears while a tolerance is less than 0.1. Table 5.1 presented the statistic of each variable.

Table 5.1 Collinearity tests for each variable

Variables	Tolerance
Quick Ratio	0.304
Current Ratio	0.301
Debt Ratio	0.433
Times Interest Earned	0.961
Working Capital / Total Assets	0.287
Fixed Assets / Total Assets	0.606
Inventory Turnover	0.766
Accounts Receivable Turnover	0.91
Fixed Asset Turnover	0.338
Total Asset Turnover	0.726
Net Income / Sales	0.794
After-tax Return on Assets	0.144 *
After-tax Return on Equity	0.139 *
Gross Profit Margin	0.822
After-Tax Net Income Growth Ratio	0.947
Sales Growth Ratio	0.945
Cash Flow Ratio	0.819
permanent capital to fixed assets ratio	0.337

* A tolerance of less than 0.2

All of the variables, except After-tax Return on Assets and After-tax Return on Equity, provided with the tolerance exceed 0.25 indicate no serious problem of collinearity. It therefore suggests that After-tax Return on Assets and After-tax Return on Equity should be excluded in developing the logistic regression model for the avoidance of collinearity.

2. *Level of fit*

After determining the levels of collinearity among variables (excluding two variables: After-tax Return on Assets and After-tax Return on Equity), the logistic regression model was then structured from the estimation sample of firms. Table 5.2 reports the levels of fit for the developed model by the –2 log-likelihood statistic.

Table 5.2 Level of fit

Variables	Incremental $-2Log-Likelihood\ \ \chi^2$ (1)
Intercept	0.131
Current Ratio	3.95 **
Debt Ratio	76.11 ***
inventory turnover	4.76 **
accounts receivable turnover	3.35 *
Fixed Asset Turnover	7.36 **
Total Asset Turnover	42.2 ***
Gross Profit Margin	14.84 ***
Sales Growth Ratio	4.01 **
Cash Flow Ratio	9.56 **
permanent capital to fixed assets ratio	9.74 **
Model –2 log-likelihood (2)	374.76 ***

Notes:

(1). The incremental $-2Log-Likelihood\ \ \chi^2$, Chi-square distribution with one degree of freedom, tests the predictive significance of each individual variable.

(2). Model –2 log-likelihood, Chi-square distribution with 15 degrees of freedom, tests the null hypothesis that the coefficients of all predictor variables in the model are zero.

Significance levels: * statistically significant at the 0.10 level

** statistically significant at the 0.05 level

*** statistically significant at the 0.01 level

The incremental $-2Log-Likelihood\ \ \chi^2$ for every variable listed in table 5.2 indicates that these variables each have significant explanatory power for the model. That is, they do contribute to predicting the financial distress. Those provide with no significantly predictive power are excluded by the stepwise procedure[2]. The –2 log-likelihood statistic for the model

[2] If the significance level of the ratio is above 0.1, the ratio was excluded by stepwise procedure. If it is lower than 0.1 but larger than 0.05, that ratio is included in the model but not in the table.

is significant, it therefore indicating the collected variables as a group predict the response variable well.

After verifying goodness-of-fit to the model, the next step will show the predictive results of the logistic regression model for comparison with that of the XCSR model.

3. *Classification Results*

The integrated results of the logistic regression model are summarized in Table 5.3. The presentation of the model's predictive power is divided into three parts: the classification accuracies (the first column), the classification error (the second and third columns), and the misclassification costs (the last three columns).

Table 5.3 Classification results of the logistic regression model

	Accurate Rate (%)	Type I error (%)	Type II error (%)	Cost Ratios		
				0.05	1	20
Training	78.1 ***	34.4	15.1	15.62	21.95	32.79
Testing	79.9 ***	23.8	18	18.16	20.07	23.32

Notes:
The last three columns represent the misclassification costs for the cost ratio shown at the top of the column.

*** The statistic calculated in (4-4) is significant at the 0.01 level.

The accurate rate represented the proportion of those correctly predicted by the logistic regression model. It is approximate 79% (78.1% in training sample, and 79.9% in testing sample). The statistic calculated in (4-4) indicates that this accuracy is significantly greater than due to chance, at the level of 0.01. That is, the resulting accuracies of the logistic regression model are statistically significant.

The Type I and Type II errors are illustrated in table 5.4. As it shows, Type I error is determined by a prediction of non-distressed while the company is actually distressed, and Type II error is determined by a prediction of distressed while the company is actually non-distressed.

Table 5.4 Type I and Type II error description

	Predicted Financial Distressed	Predicted Financial Non-Distressed
Actual Financial Distressed	Correct	Type I error
Actual Financial Non-Distressed	Type II error	Correct

From table 5.3, the Type II error is relative lower than the Type I error in both training and testing sample. The type I error was reduced from the training sample (34.4%) to the testing sample (23.8%), which indicated that the number of distressed companies accurately predicted increased from the training sample to the testing sample. But the type II error was raised from the training sample (15.1%) to the testing sample (18%), which represented that the number of non-distressed companies correctly predicted decreased from the training sample to the testing sample.

Different parties have distinct influences and perceptions of the misclassification costs caused by Type I or Type II errors. For examples, investors may consider a lower Type I error to avoid the investment loss. In contrast, management may be willing to have a lower Type II error to escape the self fulfilling prophecies [8]. Therefore, the misclassification costs were calculated under three assumptions regarding the ratio of the cost of the Type I and Type II error for different circumstances. For instances, a cost ratio of 20 (0.05) represents that the costs caused by a Type I (II) error are twenty times than that caused by a Type II (I) error and the cost ratio of one implies that the costs are equal in both errors. The misclassification cost which defined in [8], is calculated as:

$$\frac{(\text{Type I error} \times \text{distressed firms}(\%) \times \text{cost ratio}) + (\text{Type II error} \times \text{non - distressed firms}(\%))}{\text{distressed firms}(\%) \times \text{cost ratio} + \text{non - distressed firms}(\%)}$$

The last three columns in table 5.3 show the misclassification costs for different cost ratios in training and testing sample. A lower level of costs in testing sample than that in training sample is presented, except the cost ratio of 0.05.

The overall classification results are presented above, and they will compare to the XCSR model in next section.

5.2 *XCSR Model*

There is no restriction of using input variables in the XCSR model. To compare with the logistic regression model, the latter excluded two ratios in case of the effect of collinearity, and the XCSR model used all the eighteen variables as inputs.

In the second part of section 5.1, it has showed the significant variables selected by the stepwise procedure as a group would predict the response variable well. In other words, the predictive results of the logistic regression model summarized in table 5.3 could be a comparable benchmark. Therefore, this section gave the comparison between two models as follows. First of all, table 5.5 summaries the integrated results of the XCSR model, which has the same aspects as the table 5.3.

Table 5.5 Classification results of the XCSR model

	Accurate Rate (%)	Type I error (%)	Type II error (%)	Cost Ratios		
				0.05	1	20
Training	84.8 ***	19.6	12.6	12.79	15.11	19.02
Testing	86.5 ***	16.5	11.6	11.75	13.46	16.13

Notes:
The last three columns represent the misclassification costs for the cost ratio shown at the top of the column.

*** The statistics calculated in (4-4) is significant at the 0.01 level.

To compare between the results of the logistic regression model (table 5.3) and the results of the XCSR model (table 5.5), the three parts (classification accuracies, classification errors, and misclassification costs) are considered.

First, the classification rate of the XCSR model is more accurate than that of the logistic regression model either in training or in testing sample. The accuracy of the XCSR model is also significantly greater than due to chance, at the level of 0.01, which is provided with statistical significant. It indicates that the XCSR model should predict more accurately than the logistic regression model do. A statistical test will be used next section to show the XCSR model really does.

Second, since the higher accuracies in the XCSR model, whatever types of error of the XCSR model is lower than that of the logistic regression model. Therefore, the XCSR model has the advantages of lower errors to obtain lower costs caused by two types of error. From these two tables, the XCSR model has not only lower but stable costs under different cost ratios. Therefore, the XCSR model provides stakeholders of a firm with lower error costs and higher accuracies. For the overall comparison, the XCSR model has more predictive power than the logistic regression model does.

5.3 *Differences of predictive accuracy between two models*

Following from section 5.2, a paired-test is used to objectively show the differences of the accuracy between two models. It tests the null hypothesis that the mean of the differences of the accurate rates between two models is less than or equal to zero. The other details of the test were described in the part two of section 4.5. The test results summaries in table 5.6.

Table 5.6 test of differences between two models

Model	Mean (%)	Standard deviation	z statistic
M_X	86.8	0.024	1.83 *
M_L	79.9	0.017	

Notes:
M_X is the XCSR model and M_L is the logistic regression model.
* Significant at 0.05 level.

From table 5.6, it shows that the difference between two models is significant at a level of 0.05. Hence, this result rejects the null hypothesis, and then the alternative hypothesis that the mean of the differences of the accurate rates is larger than zero is accepted. It therefore indicates that the accuracy of the XCSR model is significantly higher than that of the logistic regression model. That is, the XCSR model has a greater predictive power.

5.4 *Tendency of accurate rates for the distressed companies*

The XCSR model has shown a greater predictive power including accurate rate, types of error, and misclassification costs in section 5.2 and section 5.3. For a model to predict financial distress, it is helpful to provide stakeholders of a firm with a promising trend that the predictive accuracy for distressed companies is toward upward. A linear regression model was developed to show the tendency of the XCSR model. The result reports in table 5.7.

Table 5.7 Tendency Test Result

Time(Season)	-8	-7	-6	-5	-4	-3	-2	-1	Beta
Accuracy (%)	72.2	100	55.6	100	83.3	88.9	71.4	100	0.239

Notes:
The negative value of time represents prior to the distressed event.

Time is the independent variable and accuracy is the dependent variable in this linear regression model (see part three of section 4.5). The last column in table 5.7 reports the value of Beta, the standard coefficient of independent variable *time*. The positive value of beta indicates that the XCSR model has an uptrend to predict distressed companies with time. In other words, in case a company is classified as distressed by the XCSR model in earlier time, while the model still predicts this company as a distressed one afterward, then it is worth to watch out this caution. Since the uptrend for the prediction of distressed companies, the XCSR model then provides stakeholders of a firm with a signal to pay more and more attention to those "distressed" companies indicated by the model with time.

5.5 *Regularities*

From the results and discussions above, the XCSR model has shown its superior ability to the prediction of financial distress. In addition to the predictive power, it not only provides stakeholders of a firm with the classified result but with the entire population of regularities (classifiers). The sets of regularities which are the basis to determine a company are with information available different from that provided by the logistic regression model. Examining the regularities to determine a company, stakeholders can know much more about the financial phenomena of that company and not only a “distress” or “non-distress” result. Table 5.8 gives examples of the regularities which were used to determine whether a company is distressed or not.

Table 5.8 Examples of regularities

Action	R_1	R_2	R_3	R_4	R_5	R_6	R_7
Non-Distressed					(0.6, 13.48)		(-23.27,-3.07)
		(45, 51.45)					
Distressed						(0.02, 0.04)	
			(-0.09,0.12)				
	(37.18,50.92)			(0.57,1.93)			(-23.66,-10.16)

Notes:

R_1 is Quick Ratio, R_2 is Debt Ratio, R_3 is Working Capital / Total Assets, R_4 is Inventory Turnover, R_5 is Accounts Receivable Turnover, R_6 is Total Asset Turnover, and R_7 is After-tax Return on Equity.

Table 5.8 lists two companies, one distressed and one non-distressed, determined by the XCSR model using these regularities. The blank spaces in each regularity represent don't care. Other ratios marked don't-care in these five regularities are not reported here. For the analysis of these regularities, table 5.9 presents the profiles for these ratios.

Table 5.9 Profile analyses

Group	Statistic	R1	R2	R3	R4	R5	R6	R7
Non-distressed	Mean	104.27	40.31	0.17	1.69	3.1	0.17	1.038
	S.D.	89.98	14.71	0.18	3.21	7.98	0.12	4
	Min	0.67	5.99	-0.3	-0.24	-0.7	-0.17	-23.16
	Max	549.25	80.48	0.79	29.19	150.54	0.99	23
Distressed	Mean	42.13	57.06	0.02	1.19	1.53	0.11	-6.39
	S.D.	40.13	13.73	0.22	1.36	1.32	0.01	15.58
	Min	0.8	17.26	-0.64	0	0.03	0	-145.7
	Max	340.22	94.05	0.72	11.4	10.64	0.49	44.08

Table 5.9 presents the basic, rough information of these ratios in both groups. It shows that some ratios' means are clearly distinct with each other (e.g. R1, R2), but some means are close to each other. However, those regularities in table 5.8 provide further information to distinguish these two groups. For example, the interval of debt ratio in the second regularity for the non-distressed company is (45, 51.45), which represents one of the model's criteria to identify it is non-distressed. This interval provides a range where the XCSR model "thinks" a non-distressed company' debt ratio should fall into. The interval of any ratio therefore not only clearly signal stakeholders of a firm, but represents the knowledge which the XCSR model learns from the environment.

The discussion above does not imply that the XCSR model is a univariate analysis. Actually, it combines those matched classifiers to make a decision, similar to the multivariate analysis (logistic regression model). That is, those ratios that are not marked don't care in classifiers are the basis for the XCSR model to determine a company. For instance, in table

5.8 the XCSR model predicts the company as distressed according to five ratios: quick ratio, working capital / total assets, inventory turnover, total asset turnover, and after-tax return on equity.

Therefore, for every company, the regularities "tell" stakeholders the discriminating features of that company. The XCSR model hence differs from the traditional statistical methods (e.g. MDA and logistic regression model) for financial distress prediction. The statistical methodologies take a comprehensive point of view to present the significantly discriminating variables for the whole sample, not for every individual company (table 5.2). In other words, the XCSR model enables the stakeholders as if they have an extensive sensitivity to every predicted company. Understanding of the financial phenomena to every company is therefore raised.

Consequently, the regularities extracted from the environment, represented as the knowledge what the XCSR model learned. They provided stakeholders of a firm with more interpretations about the classified company and not just with the predictive result.

Chapter 6: *Conclusions*

6.1 *Conclusions*

XCS classifier systems taking real inputs (XCSR) have proven to be an effective instrument for the prediction of financial distress. Compared with the logistic regression technique, the XCSR model made it possible to obtain better predictive results without depending on restrictive statistical requirements regarding the collinearity among the ratios. With the statistical tests it has showed more accurate than the logistic regression model. Also, the proved upward predictive tendency for the distressed companies is useful to provide the stakeholders of a firm with a caution while a company is predicted as distressed with time passed. In my opinion, the exploitation of reinforcement learning and evolutionary computation constitutes a considerably advantage for the XCSR model to provide the superiorly predictive power.

In addition to the prediction of financial distress, the regularities in the XCSR model have also shown the information about the predicted company. They represented the knowledge that the XCSR model has learned from the environment. Also, it takes a different point of view from the logistic regression model to show the discriminating variables. The latter presents the significantly explanatory variables for the whole sample. But the regularities in the XCSR model indicate the discriminating variables for individual company. It is the difference compared to the traditional statistical methods. Therefore, the regularities assist in the stakeholders of a firm to increase the understanding of the financial phenomena to every company.

Consequently, the overall results indicate XCSR classifier systems can provide stakeholders with not only superiorly predictive power but with the increased understanding about the predicted company.

6.2 *Future Works*

For the overall results obtained in this paper, some suggestions of further research are given as follows.

- The sample selected in this paper is limited in the population of listed companies. In order to promote the robustness of the XCSR model, it is suggested to extend the company type for a more complete population of corporation.
- There is a tendency of pay more and more attention on qualitative variables recently. For example, because of the Asia financial risk in 1997, corporate governance has become a quite important issue to maintain the going-concern of a company. Related legislation has made to request companies put the mechanism of corporate governance into practice. Therefore, to incorporate the relevant variables into explanatory variables may assist in disclosing the hidden information and increase the predictive power.
- Though the obtained regularities in the XCSR model have been discussed in this paper, they could be further analyzed. For example, different industry of companies would be separated to obtain individual industrial regularities. To compare distinct industries may show the difference among them. Consequently, the analysis of regularities will provide stakeholders with much more knowledge for that company.

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