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Tsui-Hua Huang
*Graduate Institute of Management, National Taiwan University of Science and Technology, Taipei, Taiwan, ROC, and*
Yungho Leu and Wen-Tsao Pan
*Department of Information Management, National Taiwan University of Science and Technology, Taipei, Taiwan, ROC*

## Abstract

**Purpose** – In order to avoid enterprise crisis and cause the domino effect, which influences the investment return of investors, the national economy, and financial crisis, establishing a complete set of feasible financial early warning model can help to prevent the possibility of enterprise crisis in advance, and thus, reduce the influence on society and the economy. The purpose of this paper is to develop an efficient financial crisis warning model.

**Design/methodology/approach** – First, the fruit fly optimization algorithm (FOA) is used to adjust the coefficients of the parameters in the ZSCORE model (we call it the FOA_ZSCORE model), and the difference between the forecasted value and the real target value is calculated. Afterward, the generalized regressive neural network (GRNN model), with optimized spread by FOA (we call it FOA_GRNN model), is used to forecast the difference to promote the forecasting accuracy. Various models, including ZSCORE, FOA_ZSCORE, FOA_ZSCORE+GRNN, and FOA_ZSCORE+FOA_GRNN, are trained and tested. Finally, different models are compared based on their prediction accuracies and ROC curves. Furthermore, more appropriate parameters, which are different from the parameters in the original ZSCORE model, are selected by using the multivariate adaptive regression splines (MARS) method.

**Findings** – The hybrid model of the FOA_ZSCORE together with the FOA_GRNN offers the highest prediction accuracy, compared to other models; the MARS can be used to select more appropriate parameters to further improve the performance of the prediction models.

**Originality/value** – This paper proposes a hybrid model, FOA_ZSCORE+FOA_GRNN which offers better performance than the original ZSCORE model.

**Keywords** Fruit fly optimization algorithm, Generalized regressive neutral network, ROC curve, Financial crisis forecast model

**Paper type** Research paper

## 1. Introduction

There are different reasons for enterprise crisis. Most enterprise crises are related to the leaders' decision-making ability, which influences the enterprises' profit and loss, and is eventually reflected in the financial statements. The poor decision-making abilities of enterprise leaders will not generate a negative influence in a short period; however, once in the case of economic downturn, the enterprises will be bankrupted due to

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improper operation, leading to the domino effect within the overall financial crisis, thus, greatly influencing investors' interests, the national economy, and even global finance. Looking back the global financial crisis in 2008-2010, since the Lehman Brothers filed for bankruptcy in 2008, the US stock market has plunged, causing the bankruptcy of about 140 banks, and resulting in the global financial storm. This crisis was deemed to be the largest global financial crisis since 1930. Provided that a financial crisis warning model can be established for the early prevention of the occurrence of crisis events, it will be helpful to reduce the influence of such events on the economy and society. In this paper, a complete set of financial warning model is established, which is aimed at initial public offering enterprises in Taiwan to forecast the possibility of enterprise crisis occurring, in order that relevant personnel can be warned and take measures before a crisis occurs. The purposes are to avoid the expansion of loss, guarantee investors' interests, and improve national competitiveness.

Generally, most investors invest according to the financial data announced by the enterprises in order to obtain returns. However, how to apply financial data to analyze enterprise operation ability has been a topical subject. The ZSCORE model proposed by Altman (1968) is the most famous bankruptcy model. Since the invention of artificial intelligence in 1957, many scholars have been devoted to applying artificial intelligence to construct financial warning models in order to improve forecast performance, and great achievements have been made.

Altman's ZSCORE model is analyzed according to the financial statement data of USA companies; it is applicable to the perfect market economy system (Merkevicius *et al.*, 2006). Taiwan is a developing region, and its market economy system requires improvement; therefore, how to improve the forecast effect of the ZSCORE model will be a key point in this paper. Moreover, this paper intends to construct an enterprise crisis warning model, where the ZSCORE method is combined with the fruit fly optimization algorithm (FOA) and the generalized regressive neural network (GRNN) of artificial intelligence, in order to improve forecast performance. In the program, first, FOA is used to determine the optimal coefficient of the ZSCORE model. A new hybrid financial warning model is created, which is called the FOA_ZSCORE model (Pan, 2011). Second, the difference between each forecast result and the actual result is taken as the dependent variable, and the GRNN, with optimized spread by FOA (we call it FOA_GRNN), are used to forecast the difference in order to create the forecast difference of the model. Finally, the forecast result of the original FOA_ZSCORE model is added to the forecast result of FOA_GRNN, which can improve forecast performance.

The remainder of this paper is organized as follows. Section 2 reviews the related works. Section 3 presents the research method and the prediction models. Section 4 discusses the empirical results. Finally, Section 5 concludes this paper with a discussion of the key findings.

## 2. Literature reviews

### *2.1 Bankruptcy forecast model created with the traditional quantitative method*

Regarding the development of the financial warning model, in the early period before computer technology was developed; the model could only be created through single-variable analysis (Beaver, 1966). The disadvantage is that a single indicator is insufficient to represent the companies' operation conditions, and there is no prudent theory. With the progress of computer technology, single discriminant analysis (DA) has been developed into multivariate discriminant analysis (MDA). In 1968, Altman (1968) applied it to create a financial early warning model, and proposed the ZSCORE model, and later, using MDA to create the model, it became the mainstream (Blum, 1974; Deakin, 1976; Edmister, 1972). In 1977, Martin (1977) initiated the Logit model for bank failure analysis. In 1980, Ohlson (1980) challenged MDA, and thought that the variances of the two groups of samples were unequal, and that the use of MDA in the case of abnormal data would influence the forecast accuracy. Thus, he adopted Logit to create the financial warning model. The results showed that the probability of crisis within one year, two years, or 1-2 years was above 92 percent. Zmijewski (1984) used the Probit model on prediction accuracy of distressed firms, and found that sampling bias manifests in sub-categories with asymptotically biased estimators when the sample proportion of a defaulted firm differs from the proportion of the population.

Frydman *et al.* (1985) created the financial crisis forecast model with a decision tree. In addition to the traditional financial data, Casey and Baetczak (1985), Gentry *et al.* (1987) took the cash flow variable as the basis for the forecast model.

### *2.2 The application of artificial intelligence in predicting bankruptcy*

Artificial intelligence was found in 1957, but it was not popular until the neural network was proposed by Hopfield (1982) in 1982. It could handle qualitative variables, adopt different types of data, and did not have to meet the assumptions of multivariate analysis. In addition, it had good learning and tolerating errors capability. Many scholars have used it to establish bankruptcy prediction models. In recent years, many scholars have further combined it with an algorithm to solve optimization problems, and used such hybrid models for forecasting, and great achievements have been made. Pan (2009) used GA to adjust the ANFIS parameter in order to forecast the difference from the real value, which had good performance in 2009. Two years later, he proposed to use FOA to optimize the spread of GRNN (Specht, 1991) and resulted in a new model termed FOA_GRNN. In order to improve the accuracy of the bankruptcy prediction, this study uses the FOA to adjust the values of the coefficients of the ZSCORE model and uses the FOA_GRNN to forecast the difference between the forecast value of the FOA_ZSCORE model and the real value of the target variable.

*2.2.1 The application of artificial intelligence in bankruptcy prediction*. Artificial intelligence is widely used in bankruptcy forecasting, such as the back propagation neural network (BPNN), the self-organizing map neural network, and other hybrid neural network topologies. In 1990 Odom and Sharda (1990) used neural network to bankruptcy forecasting. Tam and Kiang (1992) applied BPNN to bankruptcy forecasting in 1992, and the result showed that the BPNN forecasting effect was superior to DA, Logit, and K-nearest neighbor (K-NN). Serrano-Cinca (1996) latter proposed the decision support system (DSS), which is based on self-organizing feature maps, and found that the DSS outperformed Z-score analysis. Koh and Tan (1999) proposed that the application of a neutral network in bankruptcy forecasting was superior to other methods. Shin *et al.* (2004) applied support vector machines (SVM) to the problem of corporate bankruptcy prediction. The results showed the highest level of accuracies and better generalization performance than BPN when the training set size is smaller. Alam *et al.* (2000) found that both fuzzy clustering and self-organizing neural networks are promising classification tools for identifying potentially failing banks.

Recently, Ciampi and Gordini (2013) treated small enterprises as the sample to conduct credit-risk evaluation, and found that the artificial neural network (ANN) had better performance, as compared with traditional methods. In addition, many scholars used the hybrid model to improve forecast performance. For example, Khashei *et al.* (2013)

proposed the hybrid binary classification model, which is based on the basic concepts of fussy logic and ANNs, and found that the proposed models outperformed its component and other classification models, such as SVM, K-NN, and quadratic discriminant analysis. Hui Li *et al.* (2014) developed a new method that we called it the clustering-based CBR (CBCBR), which is an unsupervised process with case-based reasoning (CBR), and integrated clustering analysis regarding business failure prediction. The empirical experiment showed that the performance of CBCBR was significantly better in terms of sensitivity for identifying minority samples, and it generated high total accuracy when compared with the classic CBR, SVM, and other traditional method, such as logistic regression, and multi-variant discriminate analysis.

*2.2.2 Construction of a forecast model with algorithm and various hybrid models.* In recent years, the treatment of optimization problems by calculation processing has been used for the classified forecasting of financial crisis companies, such as FOA, particle swarm algorithms (PSO), bee colony algorithms, and ant colony algorithm (ACAs). These methods have been applied to construct various hybrid models in order to improve forecasting performance. Pan (2012) proposed a new FOA with real-time application for finding maximum and minimum values. He adopted the financial distress historical data in Taiwan to test the optimization capability of FOA and found that using this method, the spread value of the GRNN network parameter can be optimized, and the ability of bankruptcy prediction could be improved. Hsieh *et al.* (2012), reassigned the spread of each bee by applying the feature of PSO in order to improve the artificial bee colony algorithm to search for solutions to parameter optimization and obtaining accurate bankruptcy predictions.

Chen (2013) proposed the PSO-SC-ANFIS (SC is subtractive clustering) model, which uses a PSO algorithm to reduce the probability of being trapped in the local optimum, and enhances the accuracy and global search capabilities for SC-based ANFIS training on bankruptcy prediction. Zhang *et al.* (2013) proposed the fitness-scaling chaotic genetic ant colony algorithm, which is a hybrid model combining the sequential feature selection method, genetic algorithm (GA), and ACA, and is used for forecasting bankruptcy with effect better than GA, ACA, or GACA. Zhou *et al.* (2014) proposed a method using 1 norm SVM and least square SVM for direct searching and sorting characteristic value in order to optimize parameters and feature selection, which is a good method for bankruptcy classification and forecasting. Finally, Chenga *et al.* (2014) proposed the Evolutionary Least Squares Support Vector Machine Inference Model for Predicting Contractor Default Status (ELSIM-PCDS) model, which is a hybrid model based on the Minority Over-sampling Technique (SMOTE), Least Squares Support Vector Machine (LS-SVM), and Differential Evolution algorithms. It was shown that the proposed model has better forecast performance than other models.

### *2.3 FOA*

The FOA is a new swarm intelligent algorithm for optimization proposed by Pan (2011). By simulating the food searching process of a group of fruit flies, the FOA generates a group of points, each of which representing a fruit fly, around a group location whose coordinate is marked as (*InitX_axis*, *InitY_axis*). For the *i*th fruit fly in the group, denoted by *Flyi*, its coordinate ($X_i$, $Y_i$) is calculated using:

$$X_i = InitX\_axis + Random\_Value$$
$$Y_i = InitY\_axis + Random\_Value, \quad (1)$$

where the random values added to the initial X and Y coordinates give the random direction and distance to $Fly_i$ in searching for the food. Note that the coordinate of food is the coordinate of the group of flies where the optimization solution is found. According to the location of a fruit fly, the smell concentration judgment value of the fruit fly is defined. For $Fly_i$ the smell concentration judgment value $S_i$ is defined using:

$$Dist_i = \sqrt{x^2 + Y^2} \tag{2}$$

$$S_i = \frac{1}{Dist_i} \tag{3}$$

It is shown in Equation (3) that the smell concentration judgment value $S_i$ is the reciprocal of the distance of the fruit fly to the origin of the coordinate system. Based on $S_i$, the smell concentration of $Fly_i$, denoted by $Smell_i$, is calculated using:

$$Smell_i = Function(S_i) \tag{4}$$

where $Function(S_i)$ is called the fitness function and usually is the optimization target function with the independent variable replaced by $S_i$. Depending on the objective of the optimization problem, the coordinate of the fly with the maximal smell (for maximization problem) or minimal smell (for minimization problem) is selected as the coordinate of the group location of the next iteration. The coordinate of the new group location can be calculated using:

$$X_{axis} = X(bestSmell)$$

$$Y_{axis} = Y(bestSmell), \tag{5}$$

where *bestSmell* in Equation (5) represents the index of the fly with the best smell among the fruit flies in the same group. After performing the initial step, the group location is moved to the coordinate of the new group location calculated by Equation (5). Then, a new swarm of fruit flies are generated around the new group location and the same procedure is repeated for a fixed number of iteration or until the optimization target function converges. The FOA is easy to implement and efficient in finding the optimal solution of an optimization problem.

### *2.4 General regression neural network (GRNN)*

The GRNN was proposed by Donald F. Specht (1991) for constructing a prediction model using the training samples. Given a set of $n$ samples ($X_i$, $Y_i$), where $X_i$, $Y_i$ is a scalar; $X_i$, is a vector and $1 \leqslant i \leqslant n$, the predict value of an unknown vector $X$ is calculated using the following equation:

$$Y_i = \frac{\sum_{i=1}^{n} Y_i \ exp\left(-D_i^2/2\sigma^2\right)}{\sum_{i=1}^{n} exp\left(-D_i^2/2\sigma^2\right)}$$

$$D_i^2 = (X - X_i)^T (X - X_i) \tag{6}$$

In Equation (6), each training sample, $X_i$, is used as the mean of a normal distribution, also called the radial basis function. Each output $Y_i$ of input vector $X_i$ contributes a value to the output $Y$ of an unknown input vector $X$. The contribution of $Y_i$ to $Y$ is determined by the distance between vector $X$ and $X_i$. The larger the distance between $X$

and $X_i$ is, the smaller the contribution of $Y_i$ on $Y$ is. The output $Y$ can be regarded as the weighted sum of the outputs of all the samples. The spread of the normal distribution plays an important role in the regression formula. For a small sigma value, $Y$ is solely determined by the outputs of the samples whose inputs are close to the unknown input vector $X$. On the other hand, the output $Y$ approaches the average of the outputs of all samples when the sigma value becomes very large. A GRNN is show in Figure 1.

In Figure 1, each pattern neuron represents the contribution of a sample. For sample $X_i$, the activation function of its corresponding pattern neuron is $exp(-D_i^2/2\sigma^2)$, where $D_i$ is calculated by Equation (6). Note that the numerator calculates the weighted sum of the outputs of all the samples while the denominator computes the sum of all the weight of the sample outputs. Finally, the output neuron computes the normalized output by dividing the weighted sum by the summation of all the weights.

### *2.5 Optimizing GRNN by FOA*

In order to propose the GRNN optimized by FOA prediction model, this study adopted the MATLAB GRNN toolbox and the modified MATLAB program by Pan. The procedure is illustrated in the following.

First, generate a swarm of fruit flies with random initial positions, and then give them random directions and distances to look for food. The number of iterations and the population size should be set by author's experience. It is set to be 100 and 10, respectively, in this paper. Initially, the food location is unknown; therefore, each fruit fly first estimates the distance from the origin, and then calculates the value of smell concentration.

Second, substitute the spread of GRNN with the smell concentration value; input the training data, and obtain the output value of the GRNN; calculate the root mean square error of the difference between the actual output and the output of the GRNN, the smaller the better; determine the fruit fly with the maximum smell concentration, and retain the best smell concentration value of the fruit fly swarm.

Third, repeat the above-mentioned steps, except the step of generating fruit flies' initial positions. If the smell concentration of the current iteration is better than the smell concentration of the previous iteration, replace the best smell concentration with the smell concentration of the current iteration.

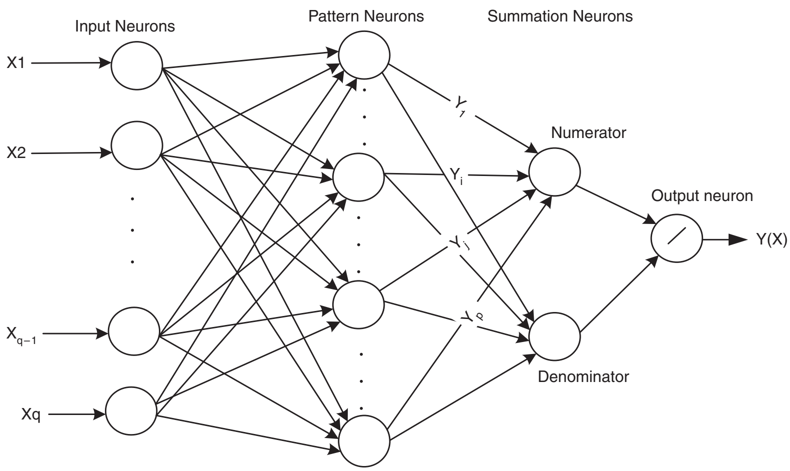



**Figure 1.**
A general regression neural network

## 3. The ZSCORE model and its improvements

### *3.1 The ZSCORE model*

The ZSCORE model was proposed by Altman (1968). In his proposal, Altman separated 66 companies among which 33 companies experienced bankruptcy and 33 companies were performing well. In total, 22 financial ratios including liquidity, profitability, leverage, solvency, and activity are included in his study. After applying the multivariate discriminate analysis on the data set, five financial ratios were selected to build the ZSCORE model, see Formula (7). In his experiment, this model provided a great prediction performance. It correctly identified 31 out of 33 companies one year before their financial troubles surfaced and 32 out of 33 financially sound companies:

$$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X5 \tag{7}$$

where Z is a Z-Score of five predictors defined in the following: $X1$ is the working capital/total assets; $X2$ the retained earnings/total assets; $X3$ the earnings before interest and taxes/total assets; $X4$ the market value equity/book value of total liabilities; and $X5$ the sales/total assets.

In an experiment of Altman (2002), data from 1969 to 1999 were used to fit the ZSCORE model and found that the best threshold for the Z-Score is 2.675. If the ZSCORE of a company is less than 2.675, the company has a great probability of going bankruptcy. This is the so-called ZSCORE model.

### *3.2 Improvement to the ZSCORE model*

If we carefully examine Formula (7) of the ZSCORE model, we would find that it is a linear regression model without a constant term. There are two ways to improvement the prediction accuracy of the ZSCORE model. First, the coefficients of the ZSCORE model may depend on the size and the composition of the market. For example, the capitalization and the constituent companies of the New York Stock Exchange (NYSE) and the Taiwan Stock Exchange (TWSE) are different. The coefficients of the ZSCORE model for the NYSE at the time when the ZSCORE model was proposed may not be suitable for the current TWSE. Furthermore, they may not be even suitable for the current NYSE. To solve this problem, we assume that the coefficients of the 5 variables in the ZSCORE model are unknown, and use the FOA algorithm to estimate the best coefficients.

To do that, we first define a new ZSCORE model as shown in the following Formula:

$$YZ = b_1X1 + b_2X2 + b_3X3 + b_4X4 + b_5X5, \tag{8}$$

where $b_i$, $i = 1$ to 5, are the coefficients to be estimated. To estimate the coefficients, we construct five groups of fruit flies in FOA, each of which is used to find an optimal coefficient of the ZSCORE model. Each group contains ten fruit flies with each fly residing in the interval of [0, 1] at both the x- and y-coordinates of the xy-plane. We use the training data to find the coefficients that minimize the root mean square error (RMSE) of the real value and the predicted value of Formula (8) for all the training examples. Note that we set the actual class value of an example to 1 if the example belongs to a bankrupt company and to 0 otherwise.

The second way to improve the ZSCORE model is to model and estimate the difference between the predicted and the real values of an example based on the input variables. Since the ZSCORE model is a linear model, the predicted value of an example will not be equal to the real value of the example unless the real value is a linear function of the input variables.

As a matter of fact, the real value of the ZSCORE model $YR$ can be written as the following formula:

$$YR = b_1X1 + b_2X2 + b_3X3 + b_4X4 + b_5X5 + \varepsilon \tag{9}$$

where the error term ε represents the non-linear part between the real value and the predicted value of an example. In this paper, we predict the error term by using a GRNN model and express the predicted value $YF$ as the following formula:

$$YF = YZ + N \tag{10}$$

where $YZ$ is the linear part and $N$ is the non-linear part of a prediction. To construct the GRNN model, we use variables $X_i$, $i = 1$ to 5, of an example as the input and the difference between the real value and the predicted value of the example as the output of the GRNN. Note that all the training examples are used in constructing the GRNN model. To predict the value of a new example $t$ with Formula (10), we use the Formula 8 to predict the linear part, $YZt$ and the GRNN to predict the non-linear part, $Nt$. Then, the predicted value, $YFt$, is calculated according to Formula (10). If $YFt$ is greater than 0.5, example $t$ is predicted as a bankrupt company; otherwise, it is predicted as a healthy company.

### *3.3 Parameter selection using multivariate adaptive regression splines (MARS)*

Since the ZSCORE model was proposed long time ago, it may not be suitable to bankruptcy prediction of the current stock markets. Especially, the financial ratios selected in 1968 may not be adequate to explain the financial distress, i.e., the bankruptcy of a company. Therefore, in this study we adopt the MARS (Friedman and Roosen, 1995) to select the most appropriate parameters for bankruptcy prediction. After applying the MARS on the 93 variables including the company information variables, financial variables, the corporate governance variables, the external rating variables, and the macroeconomic variables which are related to the prediction of the bankruptcy of a company, we selected eight most important variables as shown in Table I, for bankruptcy prediction.

The eight most important variable including Tax Rate ($X17$), TCRI Credit Rating ($X59$), Debt-Equity Ratio ($X41$), Current Ratio ($X38$), Interest Expense Ratio ($X40$), Sales Growth Ratio ($X26$), Number of Change of CPA for three years ($X79$), and the Inventory and Accounts Receivable to Equity ($X50$) Ratio. These eight variables are renamed $X1$-$X8$ in sequence. Finally, we define the revised ZSCORE (abbreviated to RZSCORE) model as shown in the following Formula:

$$RZ = b_1X1 + b_2X2 + b_3X3 + b_4X4 + b_5X5 + b_6X6 + b_7X7 + b_8X8 \tag{11}$$

The coefficients of $b_1$ to $b_8$ are determined by FOA with the training data set of a specific prediction task.

| Variable | Cost of omission | Importance | |
|---|---|---|---|
| X17 | 0.076 | 100.000 | \|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\| |
| X59 | 0.072 | 75.434 | \|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\| |
| X41 | 0.069 | 59.115 | \|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\| |
| X38 | 0.069 | 55.773 | \|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\| |
| X40 | 0.069 | 51.132 | \|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\| |
| X26 | 0.068 | 48.118 | \|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\| |
| X79 | 0.067 | 27.385 | \|\|\|\|\|\|\|\|\|\|\|\|\|\|\|\| |
| X50 | 0.066 | 25.724 | \|\|\|\|\|\|\|\|\|\|\|\|\|\|\| |

**Table I.** Variable importance

## 4. Empirical study

### *4.1 Performance metrics*

In this study, we use the ROC curve to gauge the performance of a financial crisis prediction model. Bradley (1997) pointed out that the larger the area under the ROC curve, also called the AUC of a model, the better the model is. In addition, Hand and Till (2001) pointed out that the Gini Index = (2×AUC–1) is another useful performance metric. Similarly, a larger Gini Index of a model implies that the model has better prediction accuracy.

### *4.2 Research variables and scope*

This paper adopts the historical financial data, from 2005 to 2014, of 270 companies in the TWSE stock market, which are published in the *Taiwan Economic Journal* (*TEJ*) Database. The companies belong to the same industry. The data compose of both financially healthy companies and bankrupt companies, with a ratio of 1 over 2 of bankrupt companies against healthy companies. The stratified sampling is used to divide the data set into a training data set of 216 examples and a testing data set of 54 examples. The five financial variables of Altman (1968) are used in building the ZSCORE model. All variables are normalized to the same range between 0 and 1 when constructing the FOA_ZSCORE, GRNN, and FOA_GRNN models.

### *4.3 The ZSCORE-based models*

In this study, we compare the performance of several ZSCORE-based models and the RZSCORE-based models. The first ZSCORE-based model is the original ZSCORE model. The ZSCORE value of this model can be calculated using Formula (7) and threshold is set to 2.675 for determining the type (i.e. bankrupt or healthy) of a company. The FOA_ZSCORE model is shown in Formula (8), of which the coefficients of the five parameters are determined by running the FOA on the training data set. The threshold for the FOA_ZSCORE is set to 0.5. The third model differs from the second model in that we use the FOA_ZSCORE model to predict the linear part and use a GRNN model to predict the non-linear part of the prediction. For example, suppose that the FOA_ZSCORE model predicts the ZSCORE value, i.e., the linear part of the relationship between the parameters and the target variable, of a company to be 0.6 and the GRNN predicts the non-linear part to be 0.3. The sum of the linear part and the non-linear part is 0.9. Since 0.9 is greater than 0.5, we therefore categorize the company as a bankrupt company. We call the third model the FOA_ZSCORE+GRNN model. Lastly, the fourth model, termed the FOA_ZSCORE+FOA_GRNN, differs from the third model in that we use the FOA to find the optimal spread of the GRNN model. The programs for different model are written in MATLAB. The number of iterations and population size (i.e. number of flies in a group) of the FOA are set to 100 and 10, respectively.

Figure 2 shows the curve of the root mean square of the differences between the predicted values and their corresponding real values in searching for the coefficients of the FOA_ZSCORE model. Figure 3 shows the trajectories of the best fruit flies in each group of the 100 iterations of the FOA_ZSCORE algorithm.

Figure 4 shows the RMSE of the differences between the real differences (i.e. the real non-linear parts) and the predicted differences of the FOA_GRNN in building the GRNN model for the non-linear part prediction. Similarly, Figure 5 shows the trajectories of the best fruit flies in each group of the 100 iterations of the FOA_GRNN program. Note that due to the fast convergence in searching for the best spread (i.e. standard deviation) of the GRNN model, all the best fruit flies in each group after the sixth iteration overlap at the

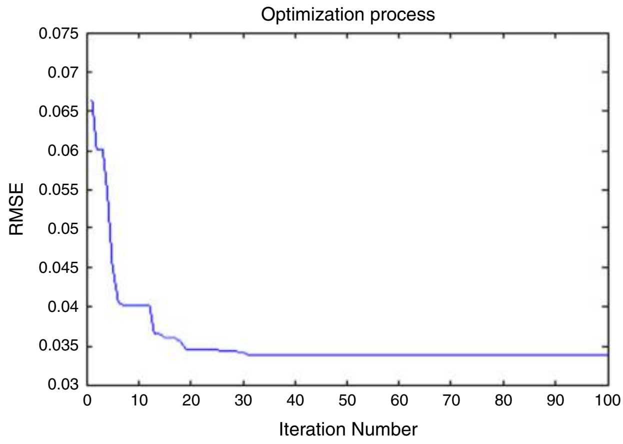



**Figure 2.**
The RMSE curve diagram of the FOA_ZSCORE

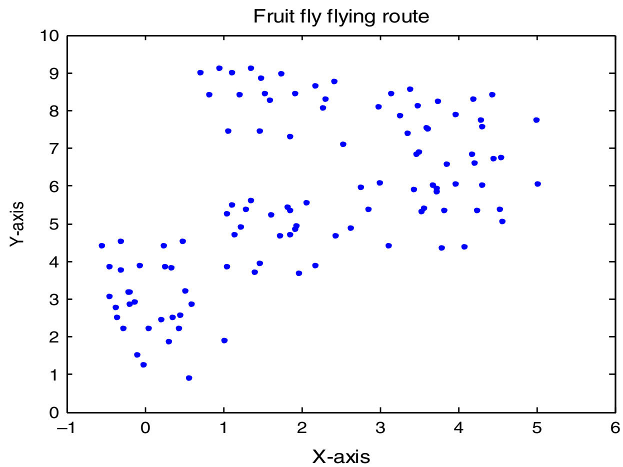



**Figure 3.**
The fruit fly trajectories in searching for the coefficients of the FOA_ZSCORE model

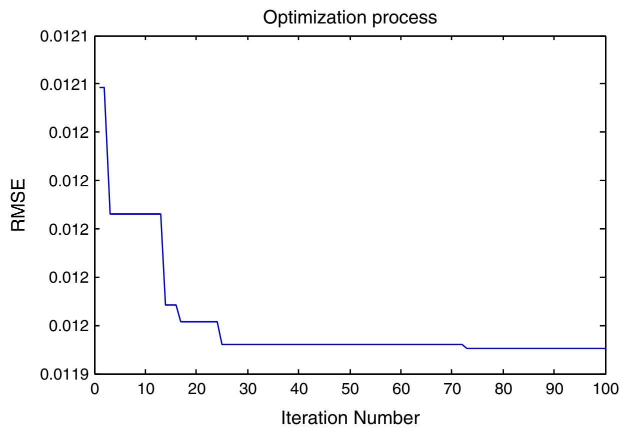



**Figure 4.**
The RMSE curve diagram of the GRNN model

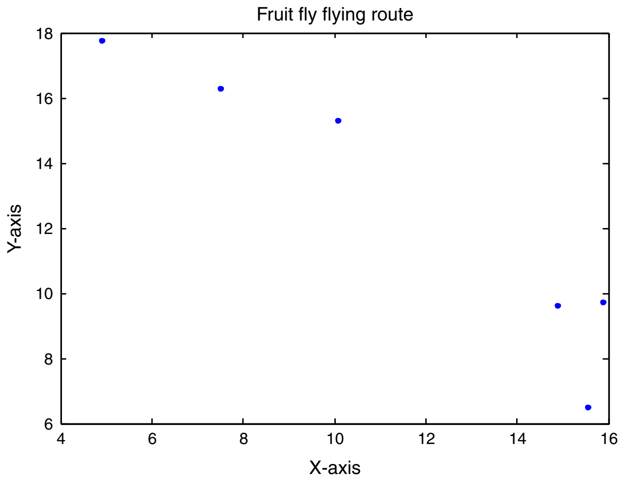



**Figure 5.**
The fruit fly trajectories in searching for the best spread of the GRNN model

same point in Figure 5. To test the effect of parameter selecting using the MARS, we replace the ZSCORE model with the RZSCORE model. That is, we replace Formula (8) with Formula (11) in all the different experiment settings. For example, by replacing the ZSCORE model with the RZSCORE model in the FOA_ZSCORE+FOA_GRNN model, we have the FOA_RZSCORE+FOA_GRNN model, and so on.

### *4.4 Performance comparison*

*4.4.1 Comparisons on prediction accuracy*. In calculating the prediction accuracies of different models, we use stratified fivefold cross-validation method. That is, we divide the 270 companies into five equal-sized partitions and within each partition the ratio of the number of bankrupt companies over the number of healthy companies is one to two. In each experiment, one partition is taken as the test data set and the rest four partitions serve as the training data set. The experiment is repeated five times and each uses a different partition as the testing data set. We denote different experiment with a series of digits. For example, 23,451 denotes the experiment in which the second, the third, the fourth, and the fifth partition are jointly used as the training data set and the first partition is used as the testing data set. The testing data set does not join in the training of the prediction model, and both the training data set and the testing data set are used to test the performance of the prediction model. Table II shows the

**Table II.**
Fivefold cross-validation of the ZSCORE-based models

| | FOA_ZSCORE +FOA_GRNN | | FOA_ZSCORE +GRNN | | FOA_ZSCORE | | ZSCORE | |
|---|---|---|---|---|---|---|---|---|
| | 1-216 (Training) | 217-270 (Testing) | 1-216 (Training) | 217-270 (Testing) | 1-216 (Training) | 217-270 (Testing) | 1-216 (Training) | 217-270 (Testing) |
| 12,345 | 0.925926 | 0.851852 | 0.666667 | 0.666667 | 0.666667 | 0.666667 | 0.5555556 | 0.5 |
| 23,451 | 0.916667 | 0.907407 | 0.666667 | 0.666667 | 0.666667 | 0.666667 | 0.5648148 | 0.462963 |
| 34,512 | 0.861111 | 0.851852 | 0.837963 | 0.814815 | 0.666667 | 0.648148 | 0.5462963 | 0.537037 |
| 45,123 | 0.884259 | 0.814815 | 0.666667 | 0.666667 | 0.666667 | 0.666667 | 0.537037 | 0.574074 |
| 51,234 | 0.884259 | 0.833333 | 0.694444 | 0.666667 | 0.666667 | 0.666667 | 0.5185185 | 0.648148 |
| AVG. | 0.8944444 | 0.8518518 | 0.7064816 | 0.6962966 | 0.666667 | 0.6629632 | 0.544444 | 0.54444 |

experimental result of the ZSCORE-based model. It shows that the FOA_ZSCORE +FOA_GRNN model achieved the highest prediction accuracies in both the training data set and the testing data set for all the experiments. The FOA_ZSCORE+GRNN is the second best model which is superior to the FOA_ZSCORE which, in turn, is better than the sheer ZSCORE model. There are several reasons for these results. First, the FOA_ZSCORE beats the sheer ZSCORE model by choosing the better coefficients for the five parameters. Second, the FOA_ZSCORE+GRNN model gain advantages over the FOA_ZSCORE model by predicting the non-linear part of the relationship between the parameters and the target variable using the GRNN model. However, the amount of improvement is minor due to the random choice of the spread of the GRNN model. Finally, the FOA_ZSCORE+FOA_GRNN outperforms the FOA_ZSCORE+GRNN by optimizing the spread of the GRNN model using the FOA.

The performance of the RZSCORE-based models is shown in Table III. The relative orders of superiority among different models are remained the same as in Table II. It also shows that each RZSCORE-based model is superior to its ZSCORE-based counterpart by selecting the appropriate parameter for bankruptcy prediction.

*4.4.2 ROC curve analysis*. The ROC curves of the four ZSCORE-based models are shown in Figure 6. Note that the ROC curves are plotted according to the testing data of the 23,451 experiment. It shows that the FOA_ZSCORE+FOA_GRNN clearly outperforms the other models. The results are consistent with the results shown in Table II. Table IV shows the Gini indices and the AUCs of the four different models. It shows that the FOA_ZSCORE+FOA_GRNN model has both a higher AUC and a higher Gini Index than those of the other models. Clearly, the FOA_ZSCORE+FOA_GRNN model offers the best prediction capability. This is evident that the utilization of the FOA tuned GRNN model to predict the non-linear part of the ZSCORE model has improved the performance of the ZSCORE model. However, the sheer GRNN model with randomly selected the spread parameter contributes little to the performance of the ZSCORE model.

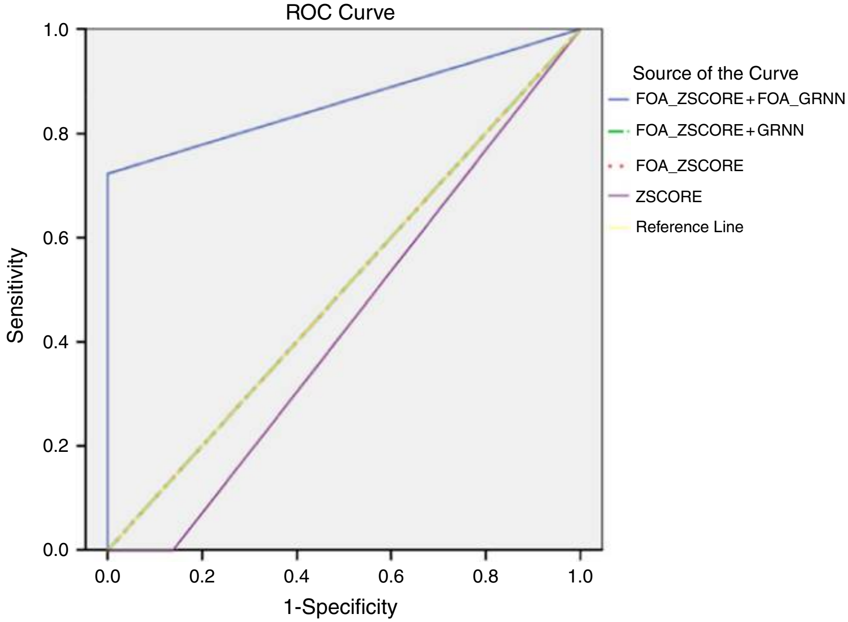
It is noted that the original ZSCORE model has been built for the USA manufacturing companies from 1946 to 1965. Due to different market environments of Taiwan and the USA, the model is not well-suited for Taiwan's market today.

The ROC curves of the three RZSCORE-based models are shown in Figure 7. It shows that the FOA_RZSCORE+FOA_GRNN is the best model.

The AUC of the FOA_RZSCORE+FOA_GRNN in Table V is 0.903, which is pretty good for a prediction task. This is evident that the parameter selection using MARS significantly improves the performance of the FOA_RZSCORE+FOA_GRNN model.

| | FOA_RZSCORE +FOA_GRNN | | FOA_RZSORE+GRNN | | FOA_RZSCORE | |
|---|---|---|---|---|---|---|
| | 1-216 (Training) | 217-270 (Testing) | 1-216 (Training) | 217-270 (Testing) | 1-216 (Training) | 217-270 (Testing) |
| 12,345 | 0.949074 | 0.851852 | 0.671296 | 0.666667 | 0.666667 | 0.6666667 |
| 23,451 | 0.949074 | 0.925926 | 0.675926 | 0.648148 | 0.680556 | 0.6666667 |
| 34,512 | 0.935185 | 0.944444 | 0.666667 | 0.685185 | 0.666667 | 0.6666667 |
| 45,123 | 0.935185 | 0.907407 | 0.680556 | 0.666667 | 0.666667 | 0.6666667 |
| 51,234 | 0.962963 | 0.888889 | 0.949074 | 0.87037 | 0.666667 | 0.6666667 |
| AVG. | 0.9462962 | 0.9037036 | 0.7287038 | 0.7074074 | 0.66944 | 0.666667 |

**Table III.** Fivefold cross-validation of the RZSCORE-based models




**Note:** Diagonal segments are produced by ties

**Figure 6.** The ROC curves of different ZSCORE-based models

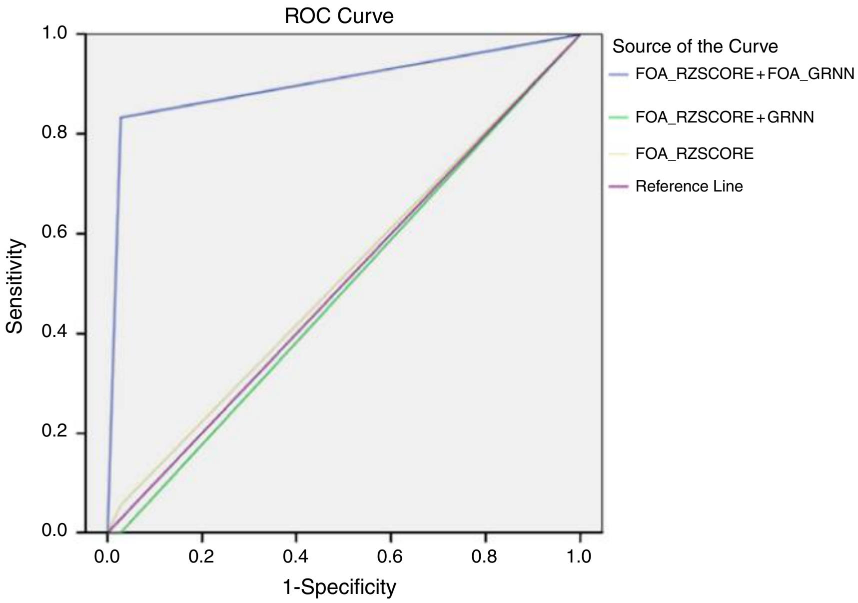
**Table IV.** Results of the ROC curve analysis of the ZSCORE-based models

| Model | FOA_ZSCORE+FOA_GRNN | FOA_ZSCORE+GRNN | FOA_ZSCORE | ZSCORE |
|---|---|---|---|---|
| Gini coefficient | 0.722 | 0.000 | 0.000 | −0.028 |
| Regional AUC | 0.861 | 0.500 | 0.500 | 0.486 |

## 5. Conclusion

In order to improve the accuracy of the ZSCORE financial crisis warning model, this study employed FOA to adjust the coefficients of the parameters in the ZSCORE model. To further promote the prediction accuracy of the ZSCORE model, we predict the difference between the forecast value of the FOA_ZSCORE model and the actual value of the target variable using a GRNN model. Since a GRNN model randomly chooses a spread value which renders sub-optimal performance, we use the FOA to find an optimal spread value for the GRNN model. Lastly, since the parameter selected in the ZSCORE model may not be suitable for a different stock market and for a different prediction time, we proposed to use the MARS method to find the appropriate parameters for bankruptcy prediction of a companies in a specific stock market at a specific time.

The empirical analysis results show that: first, to optimize the ZSCORE model with the FOA can improve the performance of the ZSCORE model; second, to divide the relationship between the parameters and the target variable into linear part and non-linear part and to predict the linear part with the FOA_RZSCORE model and the




**Note:** Diagonal segments are produced by ties

**Figure 7.** The ROC curves of different RZSCORE-based models

| Model | FOA_RZSCORE+FOA_GRNN | FOA_RZSCORE+GRNN | FOA_RZSCORE |
|---|---|---|---|
| Gini coefficient | 0.806 | −0.028 | 0.028 |
| Regional AUC | 0.903 | 0.486 | 0.514 |

**Note:** Results of the ROC curve analysis of the RZSCORE-based models

**Table V.** ROC curve analysis of the RZSCORE-based models

non-linear part with the FOA_GRNN model achieves a very high prediction accuracy; and third, the MARS can be used to select appropriate predicting variables to further boost the prediction accuracy of the ZSCORE model.

## References

Alam, P., Booth, D., Lee, K. and Thordarson, T. (2000), "The use of fuzzy clustering algorithm and self-organizing neural networks for identifying potentially failing banks: an experimental study", *Expert Systems with Applications*, Vol. 18 No. 3, pp. 185-199.

Altman, E.I. (1968), "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy", *The Journal of Finance*, Vol. 23 No. 4, pp. 589-609.

Altman, E.I. (2002), "Revisiting credit scoring models in a Basel 2 environment", in Ong, M. (Ed.), *Credit Rating: Methodologies, Rationale and Default Risk*, Risk Books, London, pp. 151-167.

Beaver, W. (1966), "Financial ratios as predictors of failure", *Journal of Accounting Research*, Vol. 4, pp. 71-111.

Blum, M.P. (1974), "Failing company discriminant analysis", *Journal of Accounting Research*, Vol. 12 No. 1, pp. 1-25.

Bradley, A.P. (1997), "The use of the area under the ROC curve in the evaluation of machine learning algorithms", *Pattern Recognition*, Vol. 30 No. 7, pp. 1145-1159.

Casey, C. and Baetczak, N. (1985), "Using operating cash flow data to predict financial distress: some extensions", *Journal Accounting Research*, Vol. 23 No. 1, pp. 384-401.

Chen, M.Y. (2013), "A hybrid ANFIS model for business failure prediction utilizing particle swarm optimization and subtractive clustering", *Information Sciences*, Vol. 220 No. 20, pp. 180-195.

Chenga, M.Y., Hoangb, N.D., Limantoa, L. and Wua, Y.W. (2014), "A novel hybrid intelligent approach for contractor default status prediction", *Knowledge-Based Systems*, Vol. 71, November, pp. 314-321.

Ciampi, F. and Gordini, N. (2013), "Small enterprise default prediction modeling through artificial neural networks: an empirical analysis of Italian small enterprises", *Journal of Small Business Management*, Vol. 51 No. 1, pp. 23-45. doi: 10.1111/j.1540-627X.2012.00376.x.

Deakin, E.B. (1976), "A discriminant analysis of predictors of business failure", *Journal of Accounting Research*, Vol. 10 No. 1, pp. 167-180.

Edmister, R.O. (1972), "An empirical test of financial ratio analysis for small business failure prediction", *Journal of Financial and Quantitative Analysis*, Vol. 7 No. 2, pp. 1477-1493.

Friedman, J.H. and Roosen, C.B. (1995), "An introduction to multivariate adaptive regression splines", *Statistical Methods in Medical Research*, Vol. 4 No. 3, pp. 197-217.

Frydman, H., Altman, E.I. and Kao, D. (1985), "Introducing recursive partitioning for financial classification: the case of financial distress", *Journal of Finance*, Vol. 40 No. 1, pp. 269-291.

Gentry, J.A., Newbold, P. and Witford, D.T. (1987), "Funds flow components, financial ratios and bankruptcy", *Journal of Business Finance and Accounting*, Vol. 14 No. 4, pp. 596-606.

Hand, D.J. and Till, R.J. (2001), "A simple generalisation of the area under the ROC curve for multiple class classification problems", *Machine Learning*, Vol. 45 No. 2, pp. 171-186.

Hopfield, J.J. (1982), "Neural networks and physical systems with emergent collective computational abilities", *Proceedings of the National Academy of Sciences*, Vol. 79 No. 8, pp. 2554-2558.

Hsieh, T.J., Hsiao, H.F. and Yeh, W.C. (2012), "Mining financial distress trend data using penalty guided support vector machines based on hybrid of particle swarm optimization and artificial bee colony algorithm", *Neurocomputing*, Vol. 82, April, pp. 196-206.

Khashei, M., Rezvan, M.T., Hamadani, A.Z. and Bijari, M. (2013), "A bi-level neural-based fuzzy classification approach for credit scoring problems", *Complexity*, Vol. 18 No. 6, pp. 46-57. doi: 10.1002/cplx.21458.

Koh, H. and Tan, S. (1999), "A neural network approach to the prediction of going concern status", *Accounting and Business Research*, Vol. 29 No. 3, pp. 211-216.

Li, H., Yu, J.L., Yu, L.A. and Sun, J. (2014), "The clustering-based case-based reasoning for imbalanced business failure prediction: a hybrid approach through integrating unsupervised process with supervised process", *International Journal of Systems Science*, Vol. 45 No. 5, pp. 1225-1241.

Martin, D. (1977), "Early warning of bank failure: a logit regression approach", *Journal of Banking and Finance*, Vol. 1 No. 3, pp. 249-276.

Merkevicius, E., Garsva, G. and Girdzijauskas, S. (2006), "A hybrid SOM-Altman model for bankruptcy prediction", *Lecture Notes in Computer Science*, Vol. 3994, pp. 364-371.

Odom, M.D. and Sharda, R. (1990), "A neural network model for bankruptcy prediction", *IJCNN International Joint Conference on Neural Network*, Vol. 2, pp. 163-168.

Ohlson, J.A. (1980), "Financial ratios and the probabilistic prediction of bankruptcy", *Journal of Accounting Research*, Vol. 18 No. 1, pp. 109-131.

Pan, W.T. (2009), "Forecasting classification of operating performance of enterprises by ZSCORE combining ANFIS and genetic algorithm", *Neural Computing and Applications*, Vol. 18, pp. 1005-1011.

Pan, W.T. (2011), *Fruit Fly Optimization Algorithm*, Tsang Hai Book Publishing Co, Taichung, Taiwan.

Pan, W.T. (2012), "A new fruit fly optimization algorithm: taking the financial distress model as an example", *Knowledge-Based Systems*, Vol. 26, February, pp. 69-74.

Serrano-Cinca, C. (1996), "Self-organizing neural networks for financial diagnosis", *Decision Support Systems*, Vol. 17 No. 3, pp. 227-238.

Shin, K.S., Lee, K.J. and Kim, H.J. (2004), "Support vector machines approach to pattern detection in bankruptcy prediction and its contingency", *Lecture Notes in Computer Science*, Vol. 3316, pp. 1254-1259.

Specht, D.F. (1991), "A general regression neural network", *IEEE Transactions on Neural Networks*, Vol. 2 No. 6, pp. 568-576.

Tam, K.Y. and Kiang, M. (1992), "Managerial applications of neural networks: the case of bank failure predictions", *Management Science*, Vol. 38 No. 7, pp. 926-947.

Zhang, Y., Wang, S. and Ji, G. (2013), "A rule-based model for bankruptcy prediction based on an improved genetic ant colony algorithm", *Mathematical Problems in Engineering*, Vol. 2013, Article ID 753251, 10pp. doi: 10.1155/2013/753251.

Zhou, L., Lai, K.K. and Yen, J. (2014), "Bankruptcy prediction using SVM models with a new approach to combine features selection and parameter optimisation", *International Journal of Systems Science*, Vol. 45 No. 3, pp. 241-253.

Zmijewski, M. (1984), "Methodological issues related to the estimation of financial distress prediction models", *Journal of Accounting Research*, Vol. 22, pp. 59-82.

**Corresponding author**
Tsui-Hua Huang can be contacted at: h11431@hotmail.com