African Journal of Business Management Vol.6 (26), pp. 7788-7798, 4 July, 2012
Available online at http://www.academicjournals.org/AJBM
DOI: 10.5897/AJBM11.2466
ISSN 1993-8233 ©2012 Academic Journals

Full Length Research Paper

A study on business performance with the combination of Z-score and FOAGRNN hybrid model

Chang-Shu Tu[1]* Ching-Ter Chang[2], Kee-Kuo Chen[3], Hua-An Lu[1]

[1]Department of Shipping and Transportation Management, National Taiwan Ocean University, Keelung, 202, Republic of China, Taiwan.
[2]Department of Information Management, Chang Gung University, Kwei-Shan, Tao-Yuan, 259, Republic of China, Taiwan.
[3]Department of Market and Logistics, Yu Da University of Business, Miaoli County, 168, Republic of China, Taiwan.

Accepted 30 January, 2012

The detection of business performance is to find out the soundness of business performance of an enterprise before the enterprise runs into any crisis or goes bankrupt in order to guard against any disaster before it happens. Generally speaking, when carrying out predicative analysis on business performance, most researchers adopt financial warning or credit rating mode. The data used are generally from events that have already happened. This paper, however, adopts a constructed business performance detection model to facilitate discrimination of business performance before the occurrence of any disaster. In this paper, the financial statements and various financial ratios of TSEC/GTSM listed fourth-party logistics providers were collected as sample data and four differential prediction models were constructed for business performance prediction of fourth-party logistics providers. Our empirical results showed that, the combination of Z-score and FOAGRNN hybrid model has differential prediction capacity significantly superior to other models, and the generalized regression neural network (GRNN) model after being adjusted with fruit fly optimization algorithm can effectively improve its prediction capacity.

Key words: Z-score, generalized regression neural network (GRNN), fruit fly optimization algorithm, particle swarm optimization, grey relational analysis.

INTRODUCTION

In the past few years, many Taiwanese private enterprises have experienced operational difficulties and/or financial crises under the impact of the mortgage crisis. Therefore, it is necessary for the operational and managerial personnel of an enterprise to propose some business performance discriminating methods with which they can find out the enterprise's business performance state before the occurrence of any crisis or bankruptcy in order to reduce the risk of bankruptcy.

However, most previous studies adopted financial warning (Lee and Chen, 2007; Salehi and Abedini, 2009) or credit rating (Duffie, 1999; Shen and Ling, 2006) as tools in their construction of performance discriminating prediction models. Thus, what the business performance of an enterprise does is to send out some warning messages before the enterprise folds up or runs into any financial difficulties. In light of this, a business performance discriminating method was proposed in this paper, which took fourth-party logistics providers as its study subjects and used 170 data sets from 5 financial variables of the Z-score model as business performance indicators to carry out grey relational analysis (GRA) on the enterprises' operation capacity. We ranked the fourth-party logistics providers in terms of operation capacity according to their grey relational grades, and assumed that the top 85 places were with good business performance in the current quarter and the last 85 places were with poor business performance. With the Z-score

*Corresponding author. E-mail: long.tree@msa.hinet.net.

model, the combination of Z-score model and generalized regression neural network (GRNN) model (referred to as Z-score + GRNN), the combination of Z-score model and FOA modified GRNN model (referred to as Z-score + FOAGRNN), and the combination of Z-score model and PSO modified GRNN model (referred to as Z-score + PSOGRNN), we constructed a business performance detecting model for the reference of operational and managerial personnel of fourth-party logistics providers.

The paper is structured as follows: introduction of motivation, objectives, and process of the study; literature review of the Z-score model, fruit fly optimization algorithm and particle swarm optimization and an explanation of the method with which the Z-score + GRNN hybrid model; analysis of the empirical results; conclusions and recommendations.

METHODOLOGY

The Z-score model

The Z-score formula for predicting bankruptcy was proposed by Altman (1968), who, during his studies from 1946 to 1965, randomly selected 66 companies with similar conditions as matched samples according to their trade and size. 33 of the companies ran into financial crisis while the other 33 were in normal financial conditions. A total of 22 financial ratios from 5 categories (Liquidity, Profitability, Leverage, Solvency and Activity) were analyzed. Multivariate discriminant analysis was used to find out the five most predictive financial ratios to get a discriminant function:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.99X_5$$

(1)

X_1 : Working capital /total assets

X_2 : Retained earnings /total assets

X_3 : Net profit /total assets

X_4 : Market value of equity /book value of total liabilities

X_5 : Sales /total assets

The calculated Z-scores are interpreted with 2.675 as the critical value. A score higher than that value represents low possibility of bankruptcy while a score lower than that value represents high possibility. The formula is also called the Z-score model.

The Z-score model has good discriminant ability and successfully discriminated 31 of the 33 bankrupt companies one year before they ran into financial crisis and 32 of the non-bankrupt companies at that time. However, formula 1 is constructed on data of U.S. bankrupt companies before 1965, while the sample data used in this study are collected from the data of Taiwanese and Chinese companies in 2005, both may be criticized as obsolete and inappropriate to use in the analysis of business performance. Therefore, it is necessary to construct a new Z-score model for predicting categorical business performance based on the available data. This paper combines the excellent linear prediction capacity of Z-score model and the nonlinear prediction capacity of GRNN model to analyze the business performance of several fourth-party logistics providers. Since GRNN has been widely used in many fields nowadays, we do not discuss it in detail here. For relevant theories, please refer to Specht (1991)'s books.

Fruit fly optimization algorithm

Fruit fly optimization algorithm (FOA) was put forward by Taiwanese scholar Pan (2011). It is a new optimization method based on fruit fly's foraging behaviors. Fruit flies are superior to other species in terms of olfactory and visual senses. They can successfully pick up various odors floating in the air with their olfactory organ; some can even smell food sources 40 kilometers away. Then, they would fly to the food. They may also spot with their sharp vision food or a place where their companions gather.

Fruit fly's foraging characteristics have been summarized and programmed into the following steps, as shown in Figure 1. The steps are:

1) Randomly generate a fruit fly swarm's initial position

Init X_axis; Init Y axis

2) Randomly assign each and every fruit fly a direction and distance for their movement to look for food with their olfactory organ.

Xi= X-axis + Random value
Yi= Y-axis + Random value

3) Since food's position is unknown, the distance (Dist) to the origin is estimated first, and the judged value of smell concentration (S), which is the inverse of distance, is then calculated.

Disti=$\sqrt{(Xi^2+Yi^2)}$; Si=1/Disti

4) Substitute the judged values of smell concentration (S) into the smell concentration judge function (also called fitness function) to get the smell concentrations (Smell) of at positions of each and every fruit flies

Smell = Function (Si)

5) Identify the fruit fly whose position has the best smell concentration (maximum value)

(best Smell best Index) = max(smell)

6) Keep the best smell concentration value and x, y coordinate; the fruit fly swarm will see the place and fly towards the position.

Smellbest = bestSmell
X_axis = X (bestIndex)
Y_axis = Y (bestIndex)

Enter iterative optimization, repeat steps II-V and judge whether the smell concentration is higher than that in the previous iteration; if so, carry out step VI. For detailed source code of the program, refer to the following website:

http://www.oitecshop.byethost16.com/FOA.html

Hybrid model construction method

Particle swarm optimization was proposed by Kennedy and Eberhart (1995), which is one type of biomimetic algorithm. It is an optimization search technique to find a solution approximating the optimized solution through iterative evolution. PSO belongs to a method that has the concept of swarm intelligence. It is derived

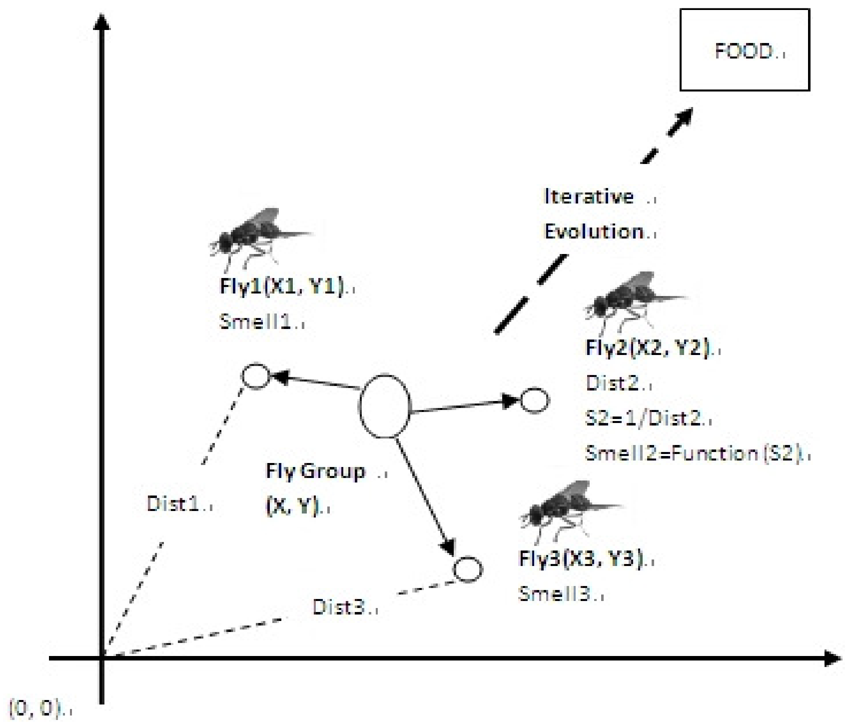

Figure 1. A schematic diagram of the evolution of fruit flies in iterative search.

from simulating the social behavior of how the bird swarm finds food, that is, when bird swarm finds food, in addition to following its own recognition to fly over better food-finding sites that have been searched before, the bird swarm also, through the cooperation and communication among swarms, knows better food-finding sites as found by other birds, finally and gradually, all the bird swarms will fly to the optimal food-finding sites.

In PSO, each bird is seen as a particle, and particle swarm can form bird swarm. When bird flies from this site to the next site, it is seen as the evolution of each iterative particle. The optimal food-finding site in the bird swarm is equal to the optimal solution appears in the particle iterative evolution process. The better food-finding site that each bird itself ever flied is the local optimum that each particle ever walked, finally, the optimal food-finding site that bird swarm wants to find is the global optimum that the particle wants to find.

Each particle has a fitness value decided by objective function, and each particle also has a speed to decide its flying direction and distance. Then all the particles will follow the currently most excellent particle to search in the solution space. PSO is initialized to be a swarm of random particles, and then through iteration, optimal solution is found. In each iteration process, the particle updates itself through following two “extreme values”. The first one is the optimal solution found out by the particle itself, and this solution is called individual’s extreme value Pbest. Another extreme value is the current optimal solution found out by the entire swarm, and this extreme value is the swarm extreme value Gbest.

Suppose in a n dimensional search space, swarm Z={ Z1,Z2,…,Zm }is formed by m particles, wherein the location of each particle Zi={ zi1,zi2,…,zin } represents a solution of the problem. Particle searches new solution through continuous adjustment of its own location Zi. Each particle can memorize the optimal solution it has searched, which is called Pid, and the optimal solution location that the entire particle swarm has passed, that is, the currently searched optimal solution, which is called Pgd. In addition, each particle has a speed, which is called Vi= { vi1,vi2,…,vin }, when all two optimal solutions are found, each particle will then, based on the following equation, update its own speed.

$$v_{id}(t+1) = \omega v_{id}(t) + \eta_1 r_1 (p_{id} - z_{id}(t)) + \eta_2 r_2 (p_{gd} - z_{id}(t))$$
$$z_{id}(t+1) = z_{id}(t) + v_{id}(t+1)$$

Wherein, ω is inertial weighting; Vid is the particle speed; η1 and η2 are non-negative constants, which are called accelerating factors; r1 and r2 are random numbers distributed in [0, 1]. To avoid the blind searching of particle, it is commonly recommended that the location and speed should be limited within certain interval (-zmax,zmax), (-vmax,vmax).

Hybrid model construction method

A close look at Z-score model’s formula 1 reveals a resemblance between it and a multiple regression model, as shown in formula 2:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \qquad (2)$$

The difference lies in that the Z-score model does not have a constant term α . In light of this, we can modify the Z-score model as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.99X_5 + \varepsilon \qquad (3)$$

Wherein ε is the error term, a random variable. Referring to the approach of Pai (2004), we change the Z-score model to as shown in formula 4:

Table 1. Descriptive statistics of financial variables of 170 Taiwanese enterprises.

	Factor	X1	X2	X3	X4	X5
Single quarter	Max	0. 3211	0. 5708	0. 0694	9. 0062	0. 3594
	Min	-0. 4257	-0. 1563	-0. 0538	0. 1660	-0. 0010
	Avg	0. 0152	0. 1948	0. 0044	2. 4322	0. 0959
	Std	0. 1499	0. 1961	0. 0163	2. 1805	0. 0934
	N	170	170	170	170	170
Accumulation	Max	0. 3211	0. 5708	0. 1647	9. 0062	1. 2648
	Min	-0. 4257	-0. 1563	-0. 2142	0. 1660	0. 0033
	Avg	0. 0152	0. 1948	0. 0104	2. 4322	0. 2140
	Std	0. 1499	0. 1961	0. 0380	2. 1805	0. 2526
	N	170	170	170	170	170

$$Z_t = L_t + N_t \tag{4}$$

Wherein L_t is the linear part, while N_t is the nonlinear part. Designate $\tilde{Y}_t$ to represent the estimation value of Z-score model at time t and ε_t to represent the estimated residual term. In this way, the residual term at time t will be:

$$\varepsilon_t = Z_t - \tilde{Y}_t \tag{5}$$

In this paper, the residual term is predicted based on the GRNN model, the FOAGRNN model and the PSOGRNN model and can be expressed in the following way:

$$\varepsilon_t = f(X_{1_{t-1}}, X_{2_{t-1}}, X_{3_{t-1}}, X_{4_{t-1}}, X_{5_{t-1}}) + \Delta_t \tag{6}$$

Wherein, f is a nonlinear function, while Δ_t is a random error term. Thus, the prediction of the hybrid model is as follows:

$$\tilde{Z}_t = \tilde{Y}_t + \tilde{N}_t \tag{7}$$

Wherein, $\tilde{N}_t$ is the prediction value of formula 6, and the linear part and nonlinear part of the prediction value results improve the overall accuracy of the business performance prediction model.

EMPIRICAL ANALYSIS

Sample data and variables

In the study, quarterly reports of a total of 170 TSEC/GTSM listed fourth-party logistics providers have been collected via China Times “Info Winner” database. Several accounting items have been selected from the financial statements according to the Z-score model and serve as independent variables in the calculation (X1-X5). Descriptive statistics of these independent variables are shown in Table 1.

A GRA program developed by Deng (1982) and a GRA Matlab program developed by Wen et al. (2006) have been adopted in the study to calculate the grey relational grade for the ranking of the fourth-party logistics providers according to their business performance. The top 85 are selected to be companies with good business performance (indicated with 5) and the bottom 85 companies with poor business performance (indicated with 0).

Matlab 7. 0 is used for analysis. In Figures 2 and 3, the more closer a dotted line gets to the ”○” symbols, the better the corresponding company’s business performance. The analysis results reveals that, the top 3 of these 170 enterprises in terms of business performance are evergreen international storage and Transp (2607) in the 3rd quarter of 2010, Sincere Navigation Corp (2605) in the 4th quarter of 2010, and evergreen international storage and Transp (2607) in the 4th quarter of 2010, respectively; while the bottom 3 are EVA Airways Corp (2618) in the 2nd quarter of 2009, EVA Airways Corp (2618) in the 1st quarter of 2009, and China Airlines Limited (2610) in the 1st quarter of 2009, respectively.

The GRA results are sorted to serve as target Z-score values (Y), and predications are made using the 1st model, that is, the Z-score model, with the 5 Z-score financial variables to get prediction values (Y). A curve diagram plotted according to the prediction values and the target values is shown in Figure 4. The close area formed by the 2 curves in the figure represents prediction error.

The differences between the prediction values and target values are then calculated. The study finds the differences roughly fall in the range between 0 and 5. Therefore it is stipulated in this paper that 5 will be used to represent any differences larger than 5 and 0 will be used to represent any differences smaller than 0. For example, if the target value (Y) is 5(that is, good business performance) and the prediction value (Y) from Z-score model is 1.2, lower than the critical value 2.675 of the Z-score model (that is, poor business performance), it would be counted as a differentiation error whose magnitude is (|5 - 1. 2|) 3. 8; if the target value (Y) is 0(that is, poor business performance) and the prediction value (Y) from Z-score model is 2. 5, lower than the critical value 2.675 of the Z-score model (that is, poor business performance), it would be counted as a correct differentiation whose error magnitude is (|0 - 2. 5|) 2. 5. This error serves as a dependent variable (Y) of the 3 GRNN models, together with the 5 financial variables (X1-X5) of the Z-score model, they make up a total of 170 sets of sample data which are divided into 5 groups. Of the 5 data groups, 4 were used for prediction model construction, 1 was used for cross validation. Three models, that is, FOAGRNN, PSOGRNN, and GRNN, were constructed respectively to predict errors. The sum of the prediction

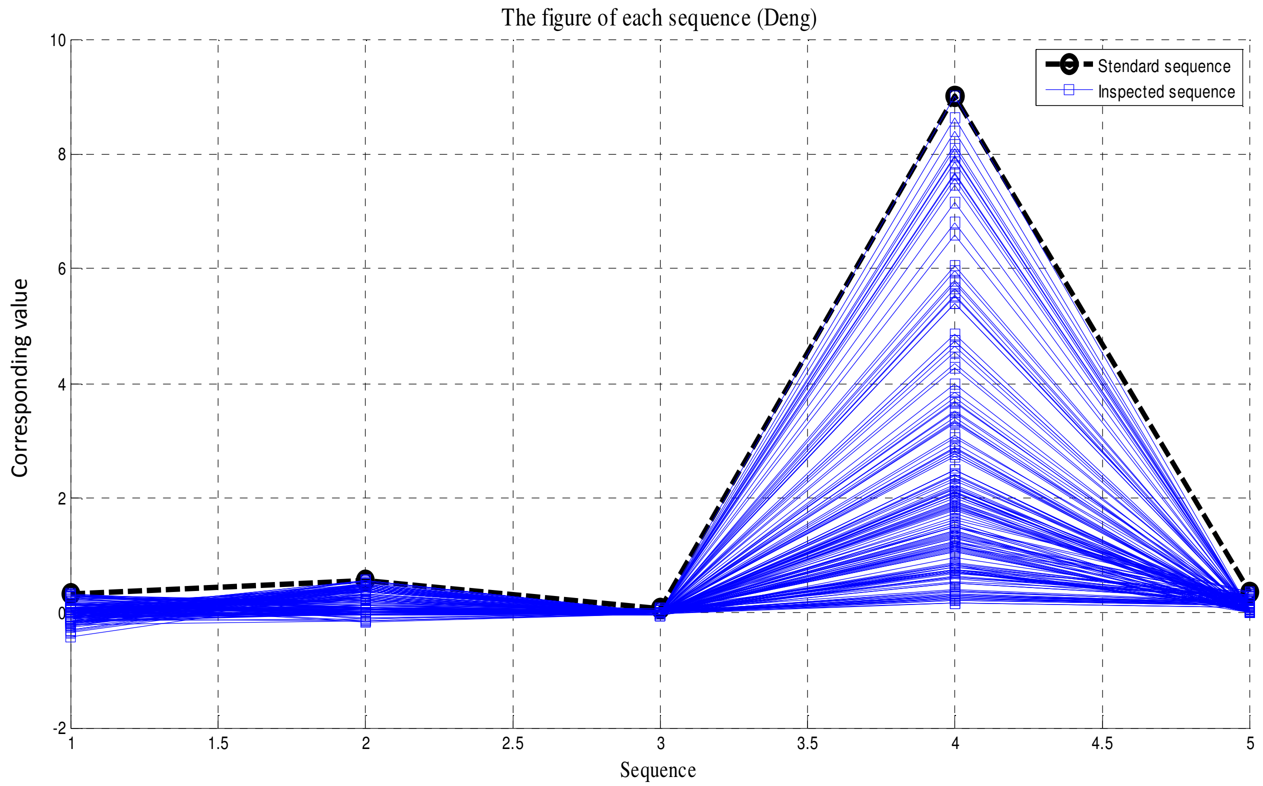

Figure 2. A schematic diagram of the GRA results of financial ratios of Taiwanese listed companies.

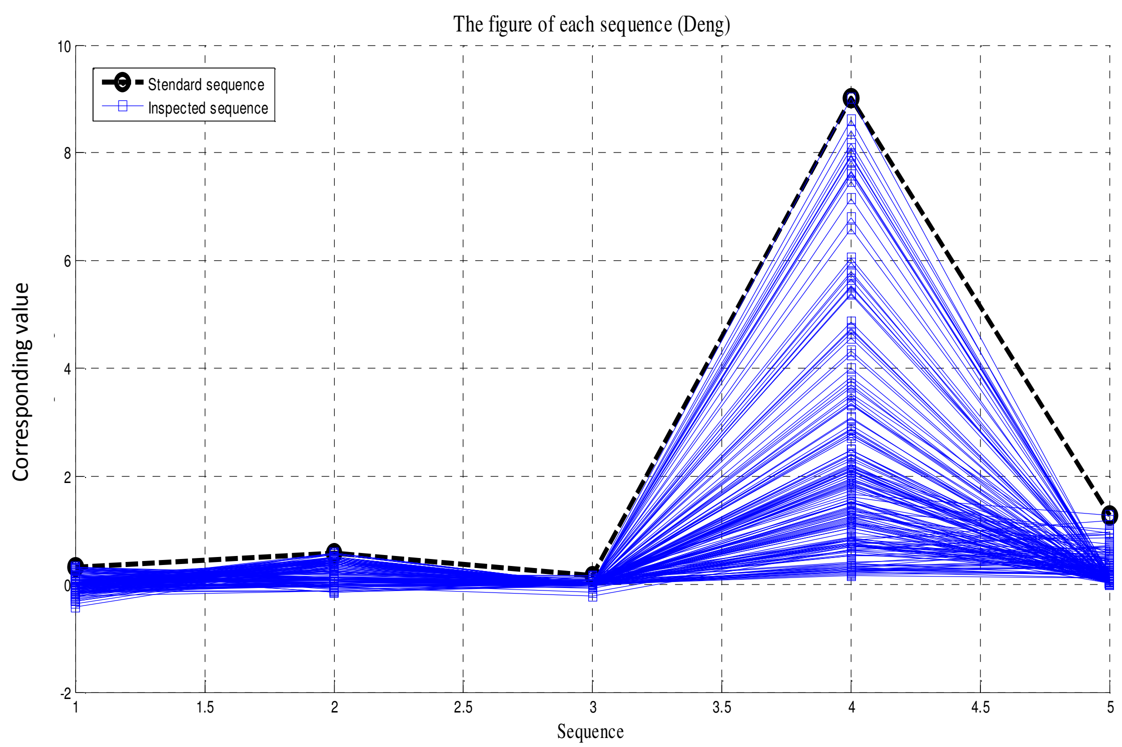

Figure 3. A schematic diagram of the GRA results of financial ratios of Chinese companies.

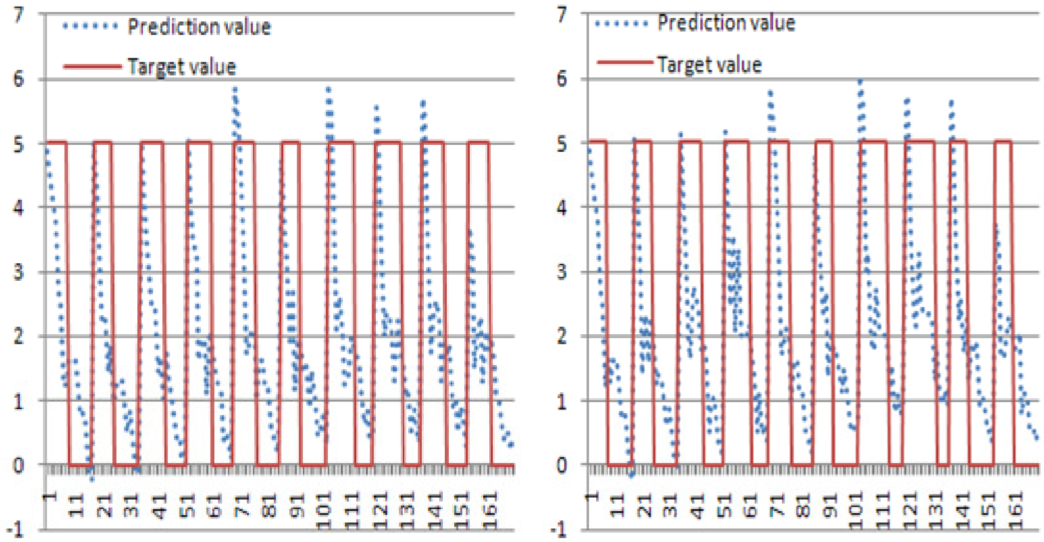

Figure 4. Diagram of the areas formed by the prediction value curve and target value curve.

value (Y) of Z-score model and the prediction results of these 3 models respectively yields 3 business performance detecting models, that is, Z-score+GRNN, Z-score+FOAGRNN and Z-score+PSOGRNN, for fourth-party logistics providers, in order to improve the Z-score model's detecting ability.

The construction of 3 hybrid models for business performance detection of fourth-party logistics providers

As for the Z-score+FOAGRNN hybrid model, the initial parameters for FOA are set in the following way: randomly generate a fruit fly swarm's initial position in the interval [0, 1] and restrict the iterative fruit flies' random flying direction and distance to the interval [-10, 10]; set the number of fruit flies in the swarm to 10 and iteration number to 100. In order to prevent overlearning of the GRNN, the termination condition of iterative search is that the RMSE becomes smaller than 0.01. To optimize GRNN with FOA, the distance between the position of each and every fly and the point of origin (0, 0) was calculated, and then inversed to get the judged value of smell concentration, which was then substituted into the spread parameter of GRNN. After that, training data were input to obtain network output, which was used in conjunction with target value to calculate RMSE (also called fitness). The smaller the RMSE, the better. In the end, the judged value of best smell concentration (S) was taken as the spread value of GRNN, and iterative search was carried out likewise with the same method. The spread parameter of GRNN can be adjusted to the best value by simulating the random foraging behavior of fruit flies which, by virtue of their olfactory and visual organs, gather at the place where the smell concentration is the best, so that the RMSE between network output and target value can be adjusted to minimum.

Figure 5 shows the single quarter financial data of the fourth-party logistics providers. The first 4 groups of data are for training the GRNN to yield output results. The upper diagram shows the flying routes of the fruit flies in their iterative searches; the lower diagram shows the convergence trend of the smallest RMSE in each iteration after the spread parameter of the GRNN was adjusted dynamically according to FOA. Results of 100 times of iteration and evolution show that the first 4 groups of data began to converge from the 60th iteration; the values of spread and RMSE were (0.0024, 0.0097) respectively. Figure 6 shows the accumulated data of the fourth-party logistics providers. The first 4 groups of data are for training the GRNN to yield output results. The upper diagram shows the flying routes of the fruit flies in their iterative searches; the lower diagram shows the convergence trend of the smallest RMSE in each iteration after the spread parameter of the GRNN was adjusted dynamically according to FOA. Results of 100 times of iteration and evolution show that the first 4 groups of data began to converge from the 20th iteration; the values of spread and RMSE were (0.0062, 0.0098) respectively.

For the Z-score+PSOGRNN hybrid model, the initial parameters for PSO are set in the following way: the spread parameter of GRNN is set to the interval of (0.001,1), the size of the swarm is set to 10 flies, and the iteration number is set to 100. Optimization of GRNN with PSO is similar to that with FOA: substitute the PSO iterative individual particles into the parameter spread of GRNN, and then input training data to get GRNN's output, which is used to calculate RMSE with the target values (also called fitness). The smaller the RMSE the better. Likewise, in order to prevent overlearning of the GRNN, the termination condition of iterative search is that

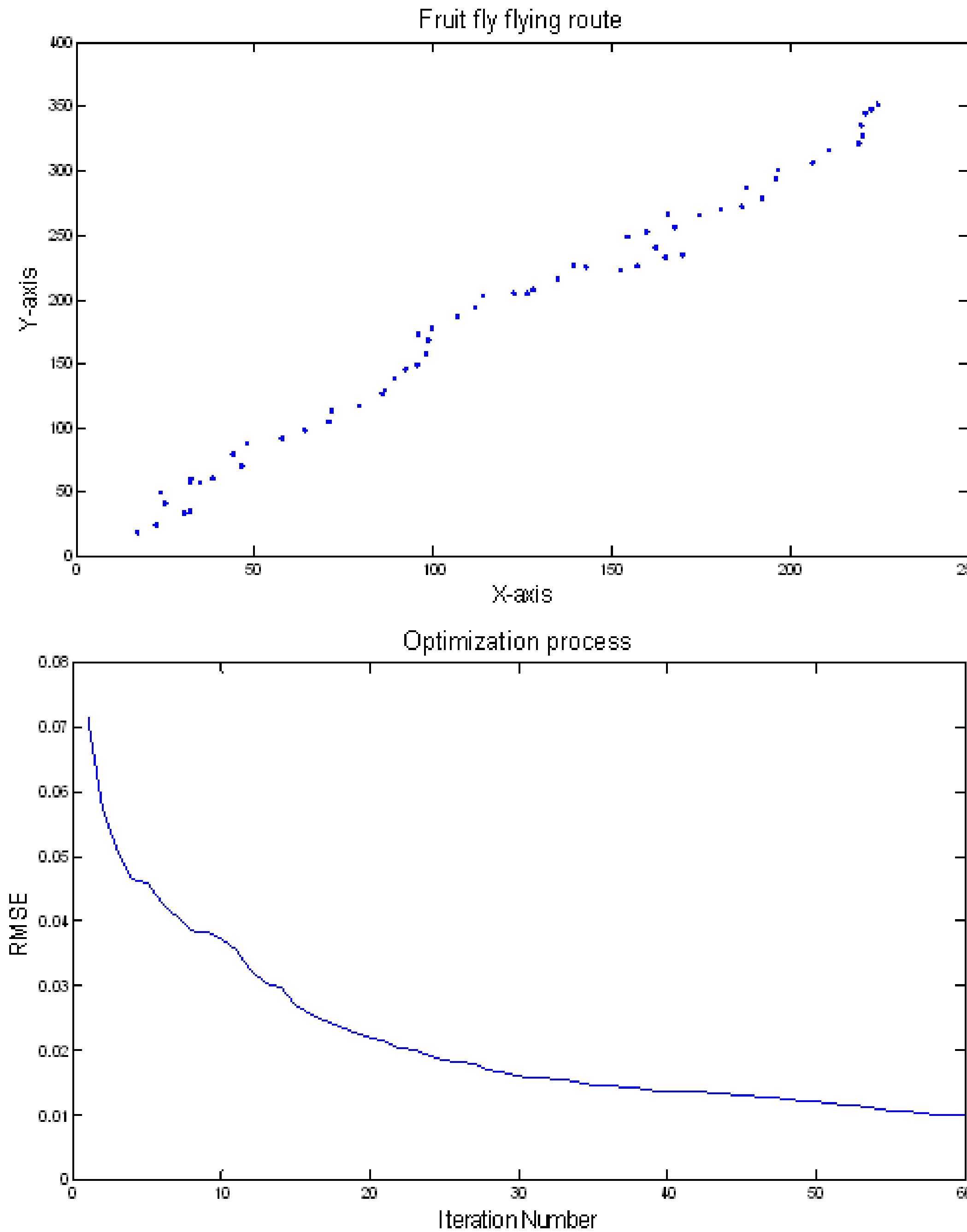

Figure 5. Using FOA and single quarter data to seek the best fruit fly flying route for spread parameter and RMSE convergence curve diagram.

the RMSE becomes smaller than 0.01. In the end, the best swarm and individual particle positions are retained, and the iterative search is carried out in this way. The spread parameter of GRNN can be adjusted to the optimal value through the bird flock's instinct to forage, so that the RMSE between GRNN's output value and target value can be minimize.

In Figure 7, the upper diagram shows the single quarter data of the fourth-party logistics providers. The first 4 groups of data are for training the GRNN to yield output results. The dynamic adjustment of GRNN's spread parameter with PSO leads to a gradually convergence trend of the smallest RMSE in each iteration. Results of 100 times of iteration and evolution show that the first 4 groups of data began to converge from the 57th iteration; the values of spread and RMSE were (0.0118, 0.0095),

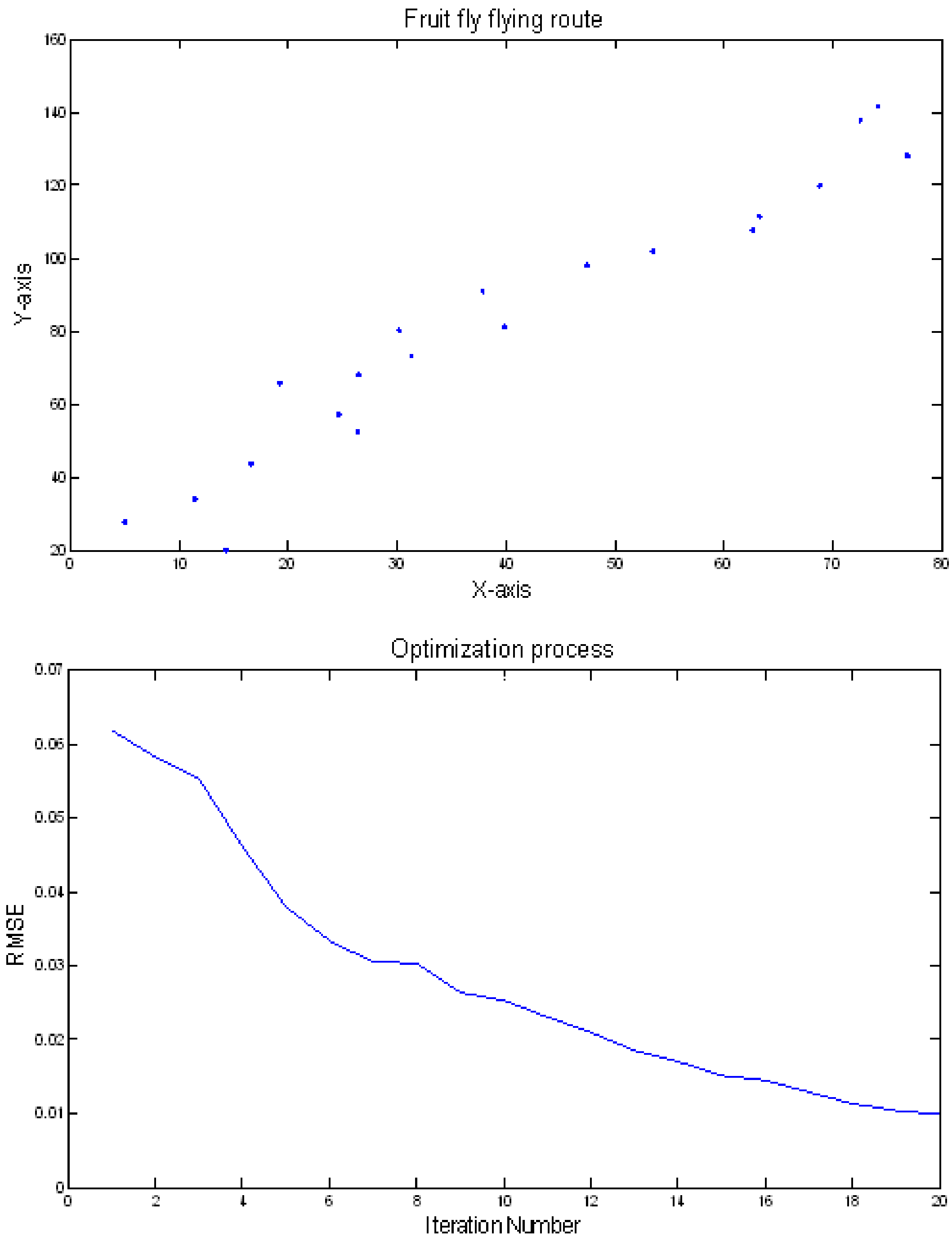

Figure 6. Using FOA and accumulated data to seek the best fruit fly flying route for spread parameter and RMSE convergence curve diagram.

respectively. In Figure 5, the lower diagram shows the accumulated data of the fourth-party logistics providers. The first 4 groups of data are for training the GRNN to yield output results. The dynamic adjustment of GRNN's spread parameter with PSO leads to a gradually convergence trend of the smallest RMSE in each iteration. Results of 100 times of iteration and evolution show that the first 4 groups of data began to converge from the 52nd iteration; the values of spread and RMSE were (0.0124, 0.0550), respectively.

Furthermore, this paper also uses general GRNN for error prediction. The spread parameter of GRNN is set to 1 and errors of the Z-score are predicted according to the single quarter data and accumulated data of fourth-party

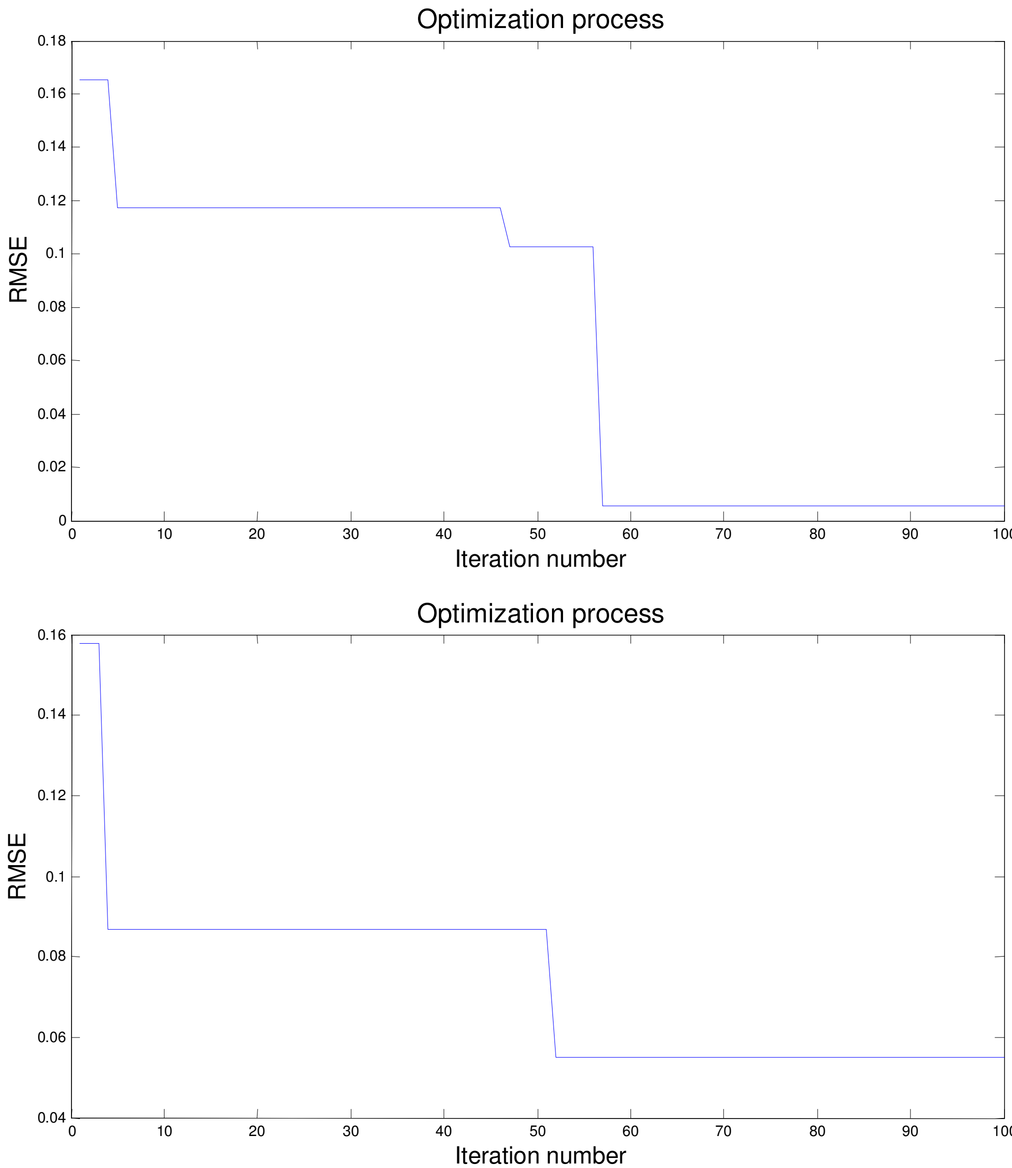

Figure 7. The convergence curve of RMSE as a result of the iterative search for optimal spread parameter during the PSO training.

logistics providers, then the prediction results of GRNN, FOAGRNN and PSOGRNN are added with the prediction results of the Z-score model respectively to get 3 business performance detecting models, i.e. Z-score+GRNN, Z-score+FOAGRNN and Z-score+PSOGRNN, for fourth-party logistics providers.

A comprehensive comparison of the four models in terms of their differential ability

In order to facilitate the plotting of ROC curve diagram, in this part of the paper 1 is used to indicate companies with good business performance, and 0 is used to indicate companies with poor business performance. Four groups of data are used for model construction prediction, and 1 group of data is used for cross validation. ROC curves are plotted using the cross validation results of 4 models, that is, Z-score, Z-score+GRNN, Z-score+FOAGRNN and Z-score+PSOGRNN, as shown in Figure 8. In the figure, the left diagram is the results of the cross validation of single quarter data, while the right diagram shows the cross validation of accumulated data. The higher an ROC curve is above the reference line, the larger the AUC and the stronger the model's differential prediction capacity (Bradley, 1997). From the two diagrams we can see that the differential prediction accuracy of Z-score model is inferior to those of the Z-

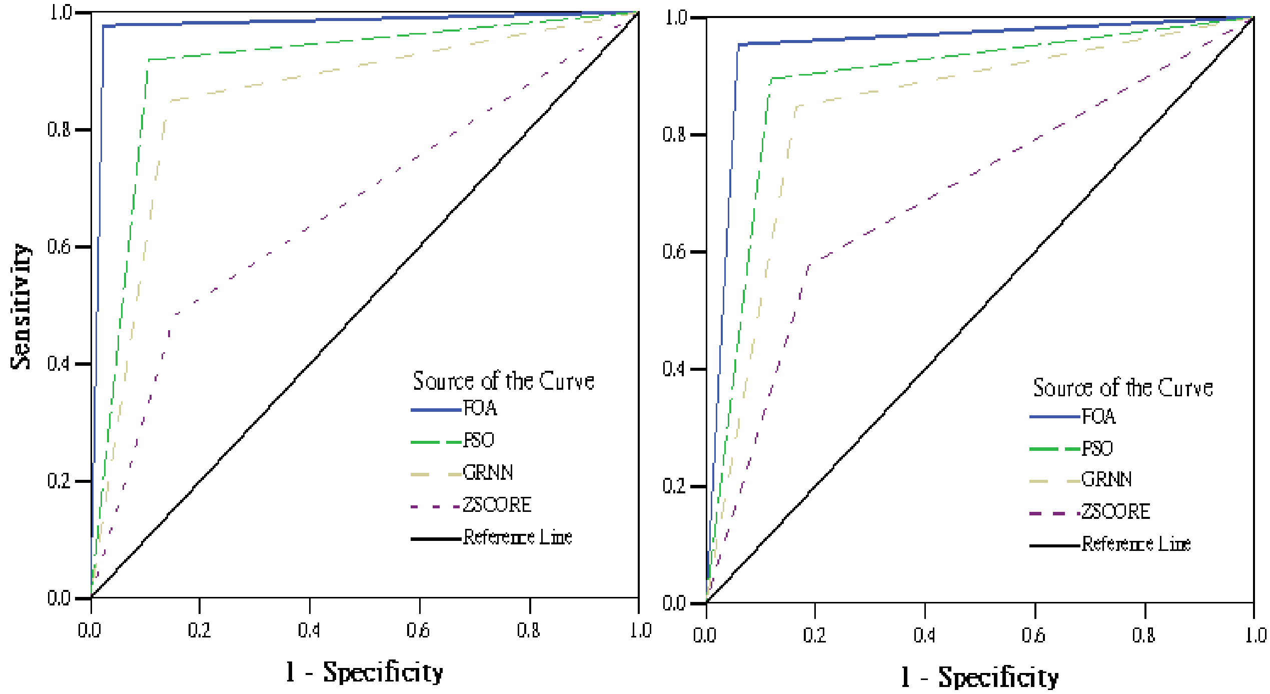

Figure 8. ROC curves plotted with the differential prediction result data from Taiwanese companies.

Table 2. Prediction result data of the 4 business performance differential prediction models.

Category	Criterion	Z-score	Z-score +GRNN	Z-score + PSOGRNN	Z-score + FOAGRNN
Single quarter data	Sen	0. 482	0. 847	0. 918	0. 976
	Spe	0. 847	0. 859	0. 894	0. 976
	AUC	0. 665	0. 853	0. 906	0. 976
	Gini Index	0. 33	0. 706	0. 812	0. 952
Accumulated data	Sen	0. 576	0. 847	0. 894	0. 953
	Spe	0. 812	0. 835	0. 882	0. 941
	AUC	0. 694	0. 841	0. 888	0. 947
	Gini Index	0. 388	0. 682	0. 776	0. 894

score +GRNN, Z-score +PSOGRNN and Z-score +FOAGRNN models; whereas the differential prediction accuracy of the Z-score +GRNN, whose parameters have not been optimized, is inferior to that of the Z-score +PSOGRNN model and the Z-score +FOAGRNN model. Meanwhile, the Z-SCORE+FOAGRNN model whose GRNN parameters are optimized with FOA is superior to the Z-SCORE+PSOGRNN model whose GRNN parameters are optimized with PSO in terms of differential prediction capacity, suggesting that FOA's optimization capacity is stronger than that of PSO. In Table 2, Sen (sensitivity) refers to the percentage of companies with a prediction result of 1 in companies with an actual value of 1; Spe (specificity) refers to the percentage of companies with a prediction result of 0 in companies with an actual value of 0.

As pointed out by Hand (2001), Gini Index= 2 × AUC–1. Table 2 shows that, whether based on single quarter or accumulated financial sample data from fourth-party logistics providers, the Z-score +FOAGRNN model has higher accuracy of prediction results in terms of specificity, sensitivity, AUC and Gini Index than other 3 models. Therefore, the model has excellent differential prediction capacity.

CONCLUSION AND RECOMMENDATIONS

This paper contributes a new FOA approach for the optimization of GRNN parameters for the reference of researchers. Furthermore, it also puts forward a method for optimizing the prediction accuracy of Z-score model that can be used in financial warning related studies by researchers. The study results show that when applied to financial sample data from fourth-party logistics providers, the Z-score model has differential prediction accuracy much lower than that of three hybrid models, that is, the Z-score +GRNN model, Z-score +PSOGRNN model, and Z-score +FOAGRNN model. Therefore, this paper takes into consideration the instability of the Z-score model's error term and this may be a feasible way to improve the Z-score model's prediction capacity. The Z-score model is suitable for prediction using linear data, whereas the GRNN model is good for forecasting with nonlinear data. It can be learnt from the analysis results of this paper that inappropriate selection of parameters of the GRNN model may lead to poor prediction results. Therefore, this paper uses the Z-score model in combination with a parameter-adjusted GRNNN model to analyze the accuracy of business performance differential prediction. The combination of two models and the optimization and adjustment of parameters of GRNN model can substantially improve differential prediction capacity. However, no comparison of differential prediction capacity has been made from the perspective of other data mining technologies such as SVM and FNN. The subject of this study also points out a direction for future studies.

REFERENCES

Altman E (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. J. Financ., pp. 589-609.

Bradley AP (1997). The use of the area under the ROC curve in the evaluation of machine learning algorithms. Pattern Recognit., 30(7): 1145–1159.

Deng J (1982). The Control Problems of Grey System. Syst. Control. Lett., (5): 288-294.

Duffie G (1999). Credit Swap Valuation. Financ. Anal. J., pp. 73-87.

Eberhart RC, Kennedy J (1995). new optimizer using particle swarm theory. Proc. Sixth International Symposium on Nagoya. Japan, pp. 39-43.

Hand DJ, Till RJ (2001). A simple generalisation of the area under the ROC curve to multiple class classification problems. Mach Learn, 45(2): 171–186.

Lee MC, Chen JF (2007). Developing financial distress classification approach based on fuzzy-rough nearest-neighbor approach. International Symposium on Advanced Intelligent Systems, Korea.

Pai PF, Lin CS (2005). A hybrid ARIMA and support vector machines model in stock price forecasting. Omega, 33(6): 497-505.

Pan WT (2011). A new fruit fly optimization algorithm: Taking the financial distress model as an example. Knowledge-Based Systems. In Press. available online.

Pan WT (2011). Fruit Fly Optimization Algorithm, Tsang Hai Book Publishing Co. Taipei.

Salehi M, Abedini B (2009). Financial distress prediction in emerging market: empirical evidences from iran. Bus. Intell. J., 2(2): 398-409.

Shen DB, Ling CM (2006). The Empirical on Valuation of Credit Default Swaps—Application of TCRI Information. Rev. Financ. Risk. Manag., 2(2): 47-74.

Specht DF (1991). A general regression neural network. IEEE Tras. Neural Networks; 2(6): 568-576.

Wen KL, Chang-Chien SK, Yeh CK, Wang CW, Lin HS (2006). Apply matlab in grey system Theory. Chuan Hwa Book CO., LTD.