African Journal of Business Management Vol. 5(30), pp. 12040-12049, 30 November, 2011
Available online at http://www.academicjournals.org/AJBM
DOI: 10.5897/AJBM11.1183
ISSN 1993-8233 ©2011 Academic Journals

Full Length Research Paper

Using particle swarm optimization (PSO) to perform financial characteristic study for enterprises in Taiwan

Jui-Ching Huang[1], Shan-Ying Wu[1] and Wen-Tsao Pan[2]*

[1]Department of Accounting Information, Kun Shan University, Taiwan, Republic of China.
[2]Department of Information Management, "Oriental Institute of Technology", Taiwan R.O.C.

Accepted 27 July, 2011

Since Particle Swarm Optimization (PSO) has properties such as: fast convergence, the ability to search global optimum and very strong universal characteritistic, it is thus very suitable to be used in clustering analysis and parameter utilization of optimized neural network by the researchers. Therefore, in this article, it is used to applied in analyzing enterprise's Financial Characteristic. First, in this article, based on the profit force and growth force of financial five forces, the financial ratio data of companies with stocks listed in regular and over-the-counter stock market in Taiwan and in financial crisis are collected, meanwhile, two normal enterprises with similar characteristics are collected for pairing purpose. Furthermore, with the aim of deriving profit force and growth force, respectively, Grey Relational Analysis is done; in the mean time, the analytical results of both of them are ranked according to grey relational grade so as to understand the performance ranking of each enterprise in profit force and growth force; then PSO is used to divide it into two groups, and the financial characteristics of these two groups of companies are compared, and the results can be used as reference by managers in the enterprises; finally in this article, three data mining techniques such as: PSO Grey Model Neural Network, Genetic Algorithm Optimized Grey Model Neural Network and general Grey Model Neural Network are used, respectively to set up Enterprise Financial Distress model and Enterprise Financial Characteristic detection model. The anlysis indicates that two different groups can be divided based on PSO. One group is enterprises that excel in profit force and growth force while the other group is enterprises that are not good at both of them. On the other hand, in Enterprise Financial Distress model and Enterprise Financial Characteristic model, the PSO Grey Model Neural Network model demonstrates the fastest convergence and the best classification capability.

Key words: Grey relational analysis, particle swarm optimization, genetic algorithm, grey model neural network, financial characteristic.

INTRODUCTION

Recently, due to rapid changes in global economic environment, Taiwan's economy remains in a turbulent and unstable period. Moreover, under the influence of Subprime Mortgage, many enterprises in Taiwan suffer bankruptcy and debt-raising risks. Settlement default may even occur occasionally at the stock market. All these phenomena demonstrate that many Taiwanese enterprises may either fail to manage the risks well or do not have full understanding of the risks involved. Therefore, it becomes imperative for managers of an enterprise to inspect the financial situations and characteristics of the (an) enterprise carefully, and prevent the possible operational risks faced by the enterprise. In this article, Taiwan's companies with stocks listed in regular and over-the-counter stock market and those with financial crisis will be used as research targets; meanwhile, normal enterprises of similar characteristics will be paired with them to perform enterprise's operation, management performance and financial characteristic analysis. First, Pan (2010) category of profit force and growth force of the five financial forces are adopted. The financial ratio data are collected from 300 companies in Taiwan with stocks listed in regular stock market and over-the-counter stock market, 100 of which are in financial crisis. Grey Relational

*Corresponding author. E-mail: teacherp0162@yahoo.com.tw.

Analysis is employed to investigate the performance ranking of profit force and growth force of each enterprise. Then, profit force and growth force was calculated based on grey relational grade value of Grey Relational Analysis, which was further analyzed through PSO Cluster. Based on grey relational grade values, enterprises are divided into two groups. The enterprise characteristics of these two groups are then studied. Finally, PSO Grey Model Neural Network (PSOGMNN), Genetic Algorithm Grey Model Neural Network (GAGMNN) and general Grey Model Neural Network (GMNN) are adopted in this article to set up Financial Distress Prediction (FDP) and Financial Characteristic Prediction (FCP) model; the classification of each modle's prediction capability is also compared. The main structure of this article is divided into four sections: The first section deal with the research motivation and the objectives of the study. The second section is introduction of PSO, Particle Clustering, Genetic Algorithm and Grey Model Neural Network and related literature. The third section introduces sample data and empirical analysis employed in this article. The final section is conclusions of the study and suggestions for further research.

METHODOLOGY

PSO algorithm and PSO cluster

Invented by professor Eberhart (1995), PSO is a random search algorithm based on group collaboration by simulating the behavior of how a flock of birds find food. It is usually regarded as one of swarm intelligences (SI) and can be included in Multiagent Optimization System (MAOS). Consider the following scenario: a flock of birds find food in a random way, and there is only one piece of food in this region. Even though all the birds may not know where the food is, they know how far they are away from the food. One simple yet effective strategy of locating the food is to search from the peripheral area that is closest to the birds. PSO finds inspiration from such a model and uses it to solve the optimization problem. In PSO, each solution to the optimization problem is like one bird's search for the solution space, which is called a particle. All particles have Fitness Values decided by optimization function, and each particle has speed deciding its direction and distance. All particles will follow the current optimal particle and search in the solution space. PSO is initialized as a group of random particles (random solutions), optimal solution is found through iteration. In each iteration, every particle updates itself with two "extreme values." One is the optimized solution found by the particle itself, called local extreme value pBest. The other is the current optimized solution of the entire swarm, called global extreme value gBest. Optionally, we can choose only the neighbors of some of the optimized particles, and then call the extreme value among these neighbors local extreme value. Matlab program is used in this study. The following steps demonstrate cluster analysis using Particle Swarm Algorithm:

Step 1: Initialize particle swarm and set up the cluster number and particle number.
Step 2: For each particle, assign it randomly to certain cluster. After all particles have been assigned, calculate the center for each cluster and then use this center for the location coding of its particles.
Step 3: Calculate the fitness of the particle, set the initial speed of the particle to 0.
Step 4: Based on fitness value, local optimized location P_{id} and global optimized location P_{gd} of the particle is generated.

$$P_{id}(i) = \{location[], fitness\}$$
$$P_{gd} = \{location[], fitness\}$$

Step 5: For each particle, update its speed and location using the following equation.

$$\begin{aligned}\text{Particle}(i), \text{velocity}[]' &= \omega \text{Particle}(i), \text{velocity}[] + \eta_1 \text{rand}()(P_{id}(i).\text{location})[] \\ &- \text{Particle}(i), \text{location}[]) + \eta_2 \text{rand}()(P_{gd}.\text{location})[] \\ &- \text{Particle}(i), \text{location}[])\end{aligned}$$

$$\text{Particle}(i), \text{location}[]' = \text{Particle}(i).\text{location}[] + \text{Particle}(i), \text{velocity}[]'$$

Step 6: Based on cluster center coding of the particle and the nearest neighbor rule, each particle is reassigned to a new cluster.
Step 7: Calculate new cluster center according to the new clustering scheme. Update fitness value for each particle.
Step 8: For each particle, update its local optimal location $P_{id}(i)$ and global optimal location P_{gd}.
Step 9: If maximum iteration number has not been reached, go back to step 5.
Step 10: Complete the operation and return to global optimal location.

Genetic algorithm

Genetic Algorithm, proposed by Holland (1975), was inspired by the Natural Selection Theory of Darwin of "Survival of the fittest through natural selection." Genetic Algorithm adopts a set of special word strings to simulate the chromosome of all species and calculate the fitness of chromosome to the environment. In each generation, each chromosome is allowed to perform crossover and mutation to generate the next generation at random; then based on the fitness of the chromosome, a choice is made on the allowance of its continuous existence. Such evolutionary alternation action will be continued until the final goal is reached. Genetic Algorithm is especially applicable to the search for question of large solution room, and question of nonlinearity, complication, possibility of noise and question with possible solution unpredictable; and this cannot be done by traditional deterministic optimization or greedy heuristics. Genetic Algorithm provides a very simple system architecture and operation process flow, but it instead can generate powerful solving and searching capability. In addition, relying on different points among the swarms, Genetic Algorithm can explore different areas at the same time. Moreover, accompanied with the characteristics of generation evolution alternation and random search, such parallel processing capability makes it difficult to get into the dilemma of local optimum. Rather, it will converge towards global optimum. All of these advantages enable Genetic Algorithm to be a new popular choice in many different fields. Important fac-tors of Genetic Algorithm include chromosome encoding, Fitness Function, selection, crossover and mutation, which will be delineated in the following.

Encoding

In Genetic Algorithm, the only one used to represent the characteristic of a problem is chromosome encoding. Most optimization problems have fixed number of variables. Hence, the most popular encoding way is to correspond these variables to certain characters or integers, encode them into fixed number of bits, and then assemble these bits to form a chromosome.

Fitness function

Fitness function is used to assess the quality represented by each chromosome, that is, its fitness. Generally speaking, Fitness function is the objective function of the optimization problem.

Selection

The selection mechanism in Genetic algorithm is to simulate the phenomenon of "survival of the fittest" in nature. That is, chromosome of high fitness will have higher survival probability while chromosome of low fitness has relatively low the survival probability. Therefore, chromosome of higher fitness might possibly have more offspring. If certain chromosomes have significantly higher fitness than those of other chromosomes, then it is likely for the former to become the main part of a group through generation alternation.

Crossover

After 2.2 selections, the selected father-generation chromosome will be done with crossover at random. The simplest crossover is one-point crossover. To be more specific, the crossover process begins with one cutting point that is selected at random from two chromosomes (A and B); then the front half section of A is associated with the back half section of B; the front half section of B is associated with the back half section of A. Such a process is used to replace the original A and B. In addition to the above-mentioned one-point crossover, there are also two-point or multiple-point crossover, but the most commonly used ones are one-point and two -point crossovers.

Mutation

Mutation operation is random mutation to simulate biological gene in nature, and usually, a very small probability (for example, 0.001) is followed to reverse certain bit. Mutation operation is helpful for Genetic algorithm to depart from partial optimum.

Grey relational analysis

Grey theory, proposed by Deng (1982), has been successfully applied in many different fields. The theory, suitable for forecast and analysis, has the characteristic of fully analyzing limited data and information so as to achieve the goal of predicting future value. Even with uncertain system and model as well as incomplete information, Grey theory can still perform system correlation analysis and model construction. Further, through forecast and decision making method, Grey theory can be utilized to investigate and understand the situation of a system. Grey Relational Analysis, Grey theory is a measurement method used to analyze the level of correlation among discrete sequence data. That is, quantitative comparison analysis is done on the development dynamics among grey system factors. It is a method for evaluating the correlation among factors according to the similarity or difference of development trend among factors. It displays all the relations among factors related to the system and thus allows people to use the results for system decision making. Forecast control provides useful information and relatively reliable base. Such an analysis model can clarify the grey relation among factors in the grey system. Meanwhile, it gives quantification measurement for system development and change trends. Currently, it is widely used in performance evaluation (Kuo, 2007; Yen, 2005; Liu et al., 2004; Li et al., 2007). For detailed theory explanation regarding grey theory, please refer to related theses and books published by Professor Chu-Lung Teng.

Grey model neural network

Grey problem means the problem of the prediction performed on the developmental change of behavioral feature value of grey uncertainty system. The original series of the feature value of the uncertain system, that is, $X_t^{(0)}$ (t=0, 1, 2,…., N-1), after one time Accumulated Generating Operation (or AGO), we can obtain new series $X_t^{(1)}$, which shows exponential growth pattern. Hence, a continuous function or differential equation can be used to perform data simulation and forecast. For the convenience of expression, the symbol is re-defined, and the original series $X_t^{(0)}$ is represented as X (t), and after one time AGO, the obtained series $X_t^{(1)}$ is represented as Y (t), and the forecast result $X_t^{*(1)}$ is represented as Z (t). The differential equation of Grey Model Neural Network model of n parameters is expressed as:

$$\frac{\mathrm{dy1}}{\mathrm{dt}} + ay_1 = b_1y_2 + b_2y_3 + \cdots + b_{n-1}y_n \tag{1}$$

In the equation, $y_2, \ldots, y_n$ is system input parameter; y_1 is system output parameter; a, b_1, b_2,…, b_{n-1} are differential equation coefficients. The time reaction equation of equation (1) is:

$$\mathrm{z(t)} = \left(y_1(0) - \frac{b_1}{a}y_2(t) - \frac{b_2}{a}y_3(t) - \cdots - \frac{b_{n-1}}{a}y_n(t)\right) +^{-\mathrm{at}} \quad \frac{b_1}{a}y_2(t) + \frac{b_2}{a}y_3(t) + \cdots + \frac{b_{n-1}}{a}y_n(t) \tag{2}$$

Let,
$$d = \frac{b_1}{a}y_2(t) + \frac{b_2}{a}y_3(t) + \cdots + \frac{b_{n-1}}{a}y_n(t)$$

Equation (2) can be transformed to Equation (3)

$$z(t) = \left((y_1(0) - d)\cdot\frac{e^{-at}}{1+e^{-at}} + d\cdot\frac{1}{1+e^{-at}}\right)\cdot(1+e^{-at}) =$$
$$\left((y_1(0) - d)\left(1-\frac{1}{1+e^{-at}}\right) + d\cdot\frac{1}{1+e^{-at}}\right)\cdot(1+e^{-at}) =$$
$$\left((y_1(0) - d) - y_1(0)\cdot\frac{1}{1+e^{-at}} + 2d\cdot\frac{1}{1+e^{-at}}\right)\cdot(1+e^{-at}) \quad (3)$$

When the transformed Equation (3) is mapped to an expanded BP neural network, we can then obtain Grey Model Neural Network of n input parameters and 1 output parameter, which are shown in Figure 1. Here, t is input parameter serial number; $y_2(t), \ldots y_n(t)$ are network input parameters; $\omega_{21}, \omega_{22}, \cdots, \omega_{2n}, \omega_{31}, \omega_{32}, \ldots \omega_{3n}$ are network weighting values; y_1 is network forecast value; LA,LB,LC and LD are used to represent, respectively four layers of Grey Model Neural Network.

Let $\frac{2b_1}{a} = u_1$, $\frac{2b_2}{a} = u_2$, …, $\frac{2b_{n-1}}{a} = u_{n-1}$, then the network initial weighting value can be represented as:

$$\omega_{11} = a,\ \omega_{21} = -y_1(0),\ \omega_{22} = u_1,\ \omega_{23} = u_2,\ \ldots,\ \omega_{2n} = u_{n-1}$$

$$\omega_{31} = \omega_{32} = \cdots = \omega_{3n} = 1 + e^{-at}$$

In LD layer, the threshold value of the output node is:

$$\theta = (1 - e^{-at})(d - y_1(0))$$

The learning process of Grey Model Neural Network is as in the following:

Step 1: Follow the training data feature to initialize network structure and to initialize parameters a and b, while, a,b values are used to calculate u.

Step 2: Follow network weighting definition to calculate $\omega_{11}, \omega_{21}, \omega_{22}, \cdots, \omega_{2n}, \omega_{31}, \omega_{32}, \ldots \omega_{3n}$

Step 3: For each input series $(t, y(t)), t = 1,2,3,\ldots,N,$ calculate the output of each layer

LA layer: $a = \omega_{11}t$

LB layer: $$b = f(\omega_{11}t) = \frac{1}{1+e^{-\omega_{11}t}}$$

LC layer: $c_1 = b\omega_{21}$, $c_2 = y_2(t)b\omega_{22},\ c_3 = y_3(t)b\omega_{23},\ \ldots,\ c_n = y_n(t)b\omega_{2n}$

LD layer: $d = \omega_{31}c_1 + \omega_{32}c_2 + \cdots + \omega_{3n}c_n - \theta_{y1}$

Step 4: Calculate the error between network forecast output and expectation output, and follow the error to adjust weighting value and threshold value.

LD layer error: $\delta = d - y_1(t)$

LC layer error:

$$\delta_1 = \delta(1+e^{-\omega_{11}t}),\ \delta_2 = \delta(1+e^{-\omega_{11}t}),\ \ldots,\ \delta_n = \delta(1+e^{-\omega_{11}t})$$

LB layer error:
$$\delta_{n+1} = \frac{1}{1+e^{-\omega_{11}t}}\left(1-\frac{1}{1+e^{-\omega_{11}t}}\right)(\omega_{21}\delta_1 + \omega_{22}\delta_2 + \cdots + \omega_{2n}\delta_n)$$

Follow forecast error to adjust the weighting value. Adjust the connection weighting value from LB to LC.

$$\omega_{21} = -y_1(0),\ \omega_{22} = \omega_{22} - \mu_1\delta_2 b,\ \ldots,\ \omega_{2n} = \omega_{2n} - \mu_{n-1}\delta_n b$$

Adjust the connection weighting value from LA to LB:

$$\omega_{11} = \omega_{11} + at\delta_{n+1}$$

Adjust threshold value:

$$\theta = (1+e^{-\omega_{11}t})\left(\frac{\omega_{22}}{2}y_2(t) + \frac{\omega_{23}}{2}y_3(t) + \cdots + \frac{\omega_{2n}}{2}y_n(t) - y_1(0)\right)$$

Step 5: Judge whether the training is ended or not, if not, go back to step 3.

In this article, parameters a, b1, b2, b3, b4, b5 and b6 of Grey Model Neural Network are performed with optimization using PSO so as to enhance the classification forecast capability of grey model neural network.

EMPIRICAL STUDY

Sample data and variables

In this article, Taiwan Economic Journal Database is used to collect 121 companies in crisis and with stocks listed in regular and over-the-counter stock market from 1995 to 2009. Each crisis company with two normal companies of the same industry is compared. Thus, the financial ratio data is from 399 companies. Since enterprises with defective value are deducted from the sampling, the final research sample contains 300 enterprises. However, given that the data for selection is based on profit force and growth force of financial five forces, the main objective is to analyze the performance and different

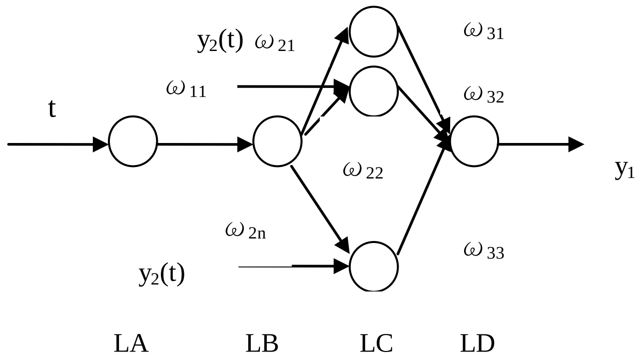

Figure 1. Grey model neural network topological structure.

Table 1. Descriptive statistical values of the financial ratio of 300 enterprises in Taiwan.

Financial ratio	X1	X2	X3	X4	X5	X6
Max	126.610	100.000	39.930	319.910	128.320	155.150
Min	-90.570	-115.470	-209.730	-99.640	-58.580	-91.780
Avg	-0.802	13.547	-0.958	6.342	4.396	-0.337
Std	16.087	17.816	23.199	35.467	21.293	23.983
N	300	300	300	300	300	300

characteristic of each enterprise in profit force and growth force. These ratios include Return on Equity (X1), Gross Profit Margin (X2), Operating Profit Ratio (X3), Revenue Growth Rate (X4), Total Asset Growth Rate (X5) and Equity Growth Rate (X6). The descriptive statistical values of these ratio data are as shown in Table 1. In this article, sample data is divided into two groups. One group contains six financial ratios to be used as independent variables (X), then associated with dependent variable (Y) that normal company (represented by 0) or company in crisis (represented by 1) ; the other group consists of six financial ratios as independent variables (X), then asso-iate with financial characteristic as dependent variable (Y). Moreover, these two sets of data are further divided into three subgroups with each contains 100 data. Besides, cross verification is done in a way that two subgroups of data are used for training the model whereas the other one subgroup of data is used to test the model stability. Table 1 shows the descriptive statistical values of these six financial ratio data.

Using grey relational analysis to perform the performance analysis of profit force and growth force

In this article, Grey Relational Analysis, proposed by Deng (1982), and grey relation Mat lab toolbox, developed by Wen et al. (2006), are used to find out grey relational grade. Then the performance analysis of profit force and growth force of financial five forces I s made. First, aiming at three indexes of profit force of 300 Taiwan's companies, including Return on Equity (X1), gross profit margin (x2) and operating profit ratio (X3), enterprise operation profit force performance assessment is done. It should be noted that all these three index values are the larger the better. In this article, the maximal values of these three indexes are used as standard sequence, and the grey relational analysis result is shown in Figure 2. The bold dotted line at the uppermost side of Figure 2 represents standard sequence while the rest fine solid lines represent inspected sequence, that is, each of the rest of the data. Each data has three nodes to represent three indexes of that enterprise. If inspected sequence is closer to standard sequence, it means that the performance of the business operation profit force of that enterprise is better. Similar to profit force, grey relation Mat lab toolbox is reused for the following two major purposes: first, to calculate the three indexes of growth force of 300 companies in Taiwan, that is, Revenue Growth Rate (X4), Total Asset Growth Rate (X5) and Equity Growth Rate (X6); second, to perform performance assessment of enterprise operation growth force.

As for the values of these three indexes, it should be noted that the larger of the values, the better. Likewise, the maximum values of these three indexes are used as standard sequence, and the Grey Relational Analysis result screen is shown in Figure 3. In figure 3, the uppermost bold dotted line represents standard sequence; the other fine solid lines represent inspected sequence, (that is, each of the rest data). Each data has three nodes to

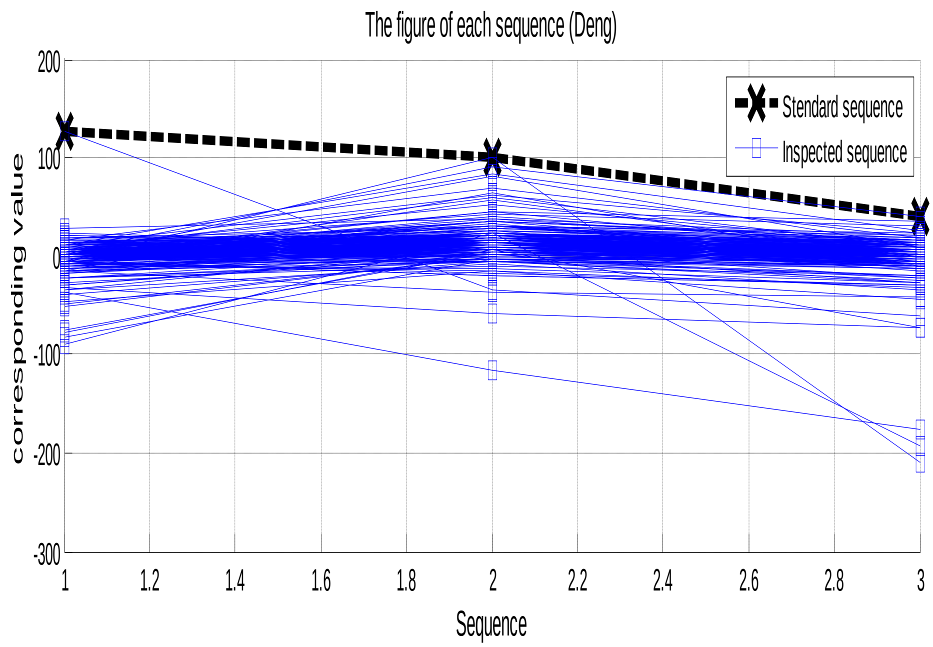

Figure 2. Using grey relational analysis to investigate sequence distribution chart generated by profit force.

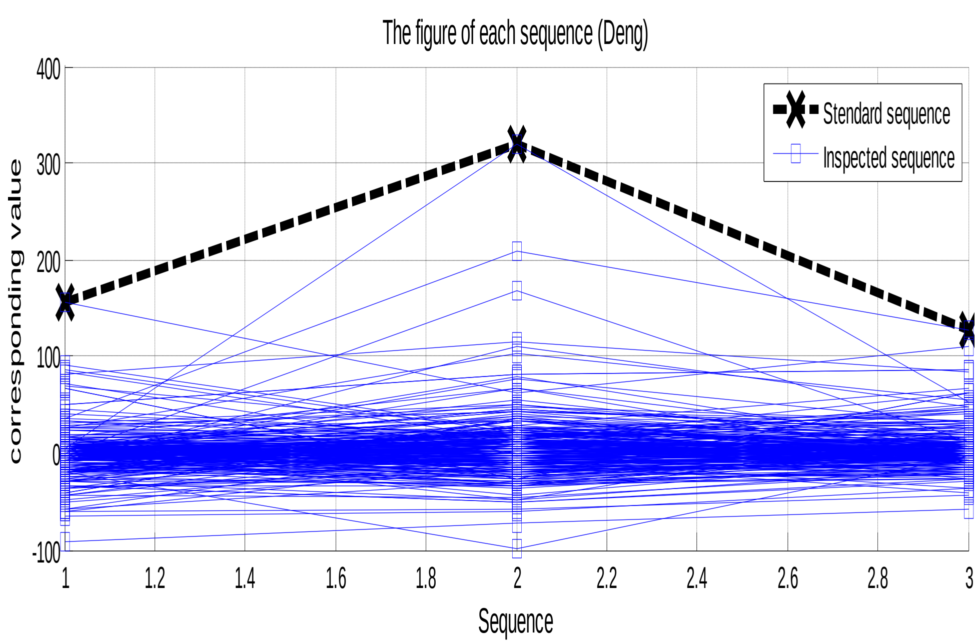

Figure 3. Using grey relational analysis to investigate sequence distribution chart generated by growth force.

represent three index values of an enterprise. If inspected sequence is closer to standard sequence, it means that the future growth force performance of that enterprise will be better. The analyses indicate that enterprises of the first three rankings in profit force are Cyber Link (5203), GT-Grou (3085) and The Landis Hotel T aipei (5703) whereas enterprises of the first three rankings in growth force are ChangHo (1468), Juh Lien (5002) and TafFeta (1454). It is hoped that the results of our analyses can be used as reference by the researchers. This study use the grey relational grade value of this analysis to perform Self-Organized Map clustering analysis so as to

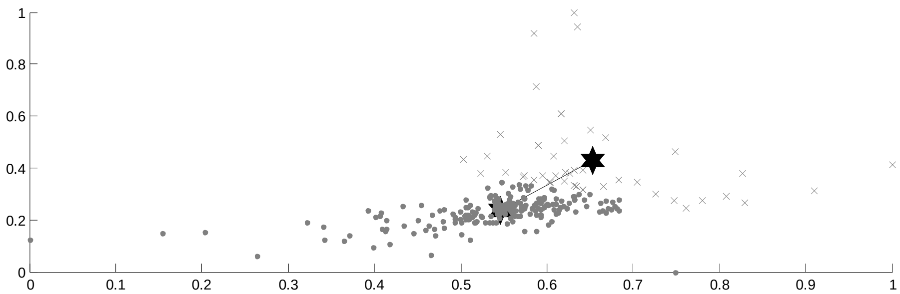

Figure 4. PSO clustering analysis result illustration.

investigate the financial characteristic of each enterprise in profit force and growth force.

Using particle swarm optimization to perform enterprise financial characteristic analysis

The grey relational grade values of profit force and growth force in section 3.2 are performed again with PSO. The method is to use Mat lab toolbox to self-write program and to divide the clustering results into two clusters. Furthermore, the financial characteristics within each cluster are also investigated. The particle swarm optimization is plotted as distribution chart in Figure 4. The hexagonal star shape in the figure is clustering center, which is represented in vector way as in the following. [0.5457 and 0.2365], [0.6535 and 0.4305]. As far as the clustering results are concerned, there are two possibilities. The first type is all good or all bad at both profit force and growth force; for the second type, one group is has good profit force but bad growth force whilst the other group is of good growth force and bad profit force. Based on the data of these two groups, one group is all good at both profit force and growth force, and the other group is all bad at both profit force and growth force. In this study, enterprises that are all good at both profit force and growth force are represented by 0 for a total of 192 data; the other group is represented by 1 with a total of 108 data as dependent variables; 6 financial ratios are used as independent variables. A total of 300 data are used for the construction of three financial characteristic models as shown in the next section.

Construction of three financial distress prediction (FDP) models and financial characteristic prediction (FCP) models

In this section, PSOGMNN, GAGMNN and general GMNN are adopted, respectively to perform the construction of FDP and FCP model. Since Grey Model Neural Network architecture is confirmed according to the dimension of input and output data, the input data dimension in the present study contains six dimensions (X1-X6) whereas output has one dimension (that is, normal company or company in crisis). Therefore, Grey Model Neural Network structure is 1-1-7-1. Here LC layer has 7 nodes, from 2 to 7; X1 to X6 financial ratio data are entered, respectively, and the output is dependent variable (Y). The first two subgroups data are entered into Grey Model Neural Network model structure to perform training, and 7 parameters in the network include a, b1, b2, b3, b4, b5 and b6, which are represented by population of particle number of 7 as regenerated at random by PSO; then based on fitness value, iteration dynamic adjustment is done, and 7 Grey Model Neural Network parameters are then optimized. Mat lab 7.0 software is further adopted to self-write the program. In the program execution process, the maximal iteration number is 100, the swarm scale is 20, initial particle location and speed. The segmental program code is in the following. % initialization iteration number, group size, particle and speed maximum and minimum value maxgen=100; sizepop=20; popmax=5; popmin=-5; Vmax=1; Vmin=-1; % initialization particle and speed, particle number is 7. x(i,:)=5*rands(1,7); V(i,:)=rands(1,7).

In generation evolution process, the output value and objective value of Grey Model Neural Network is used to follow Root Mean Squared Error (RMSE) to calculate the objective function; meanwhile, reciprocal is used to transform it into fitness value. As a result, such dynamic adjustment is performed on the parameter until the iteration is completed. In the initial parameter part of Grey Model Neural Network, the learning rate of u1, u2, u3, u4, u5, u6 is set up to be 0.0015. Similarly, in optimization parameters a, b1, b2, b3, b4, b5, b6 of Genetic Algorithm, the study has generated at random a population with individual number of 7 for its representation. Further, fitness value is followed to perform dynamic adjustment on the genetic generation. This article has adopted Mat lab 7.0 software accompanied with Genetic Algorithm Optimization Toolbox developed by Sheffield university to self-write the program. During the program execution process, the maximum genetic generation number is 100, group scale is 20, crossover rate is 0.8 and mutation rate is 0.05. After execution, roulette selection method is also adopted and elitism is taken with evolution termination

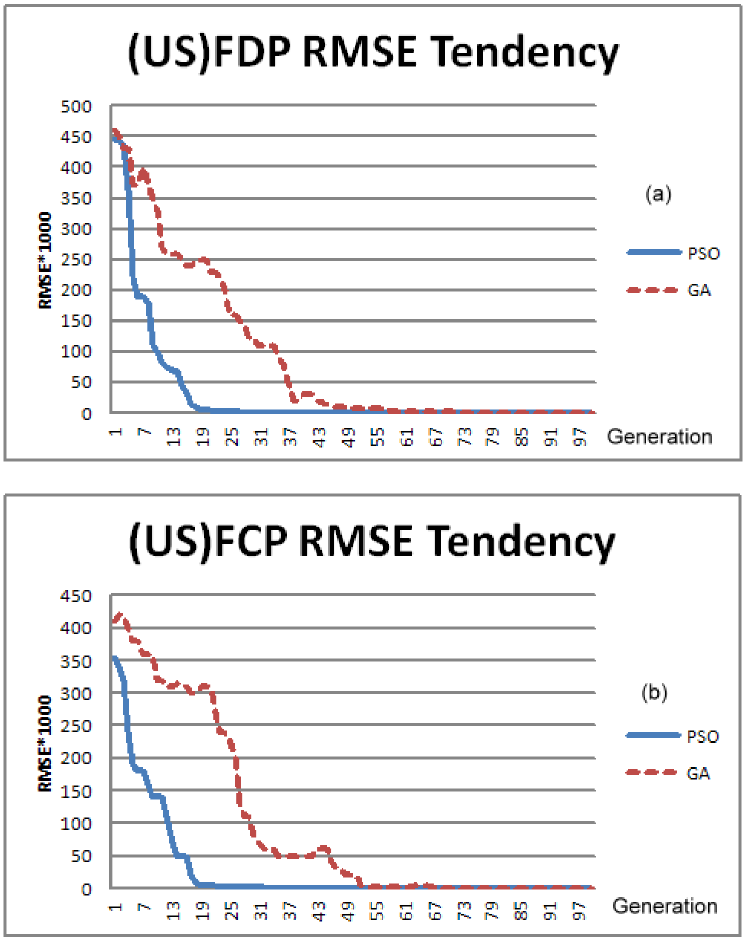

Figure 5. The parameter evolution trend of GAGMNN and PSOGMNN (FDR RMSE Tendency).

condition of the generation number. The segmental program code is shown in the following. Percentage of initialization iteration number, group size and individual number and length. maxgen=100; sizepop=20; Nind=7; Lind=10; % initialization group, individual number is 7. FieldD=[10;-1;2;1;0;1;1];Chrom=crtbp(Nind, Lind);Variable=bs2rv(Chrom, Field).

In generation evolution process, the output value and objective value of Grey Model Neural Network is used to follow RMSE to calculate objective function. Reciprocal is used to transform it into fitness value. Accordingly, such dynamic adjustment is made to the parameter until the generation number is completed. In the initial parameter part of Grey Model Neural Network, the learning rate of u1, u2, u3, u4, u5 and u6 is set up to be 0.0015. Figure 5 shows that after 100 generations, PSO and Genetic Algorithm dynamically adjust 7 parameters, and RMSE show a trend of gradual convergence. In order to let the change of each parameter be clearly seen in generation evolution process, RMSE is multiplied by 1000 times. Based on the research results, it can be seen that when FDP model adopts PSO, at generation number of 41, RMSE has minimum of (0.0007266). On the other hand, as for Genetic Algorithm, at the 76th generation has minimum RMSE (0.0009505). Moreover, when Financial Characteristic Prediction model adopts PSO, at the 47th generation has minimum RMSE (0.0005207), but for Genetic Algorithm, at the 83th generation number has minimum RMSE (0.0008355). Therefore, whether it is Financial Distress Prediction model or Financial Characteristic Prediction model, the RMSE values of PSO Grey Model Neural Network are all lower than those of Genetic Algorithm Grey Model Neural Network model. Additionally, the convergence speed of RMSE value of PSO Grey Model Neural Network is also noticeably faster than that of Genetic Algorithm Grey Model Neural Network model, and such a characteristic deserves researchers' attention. Table 2 shows, respectively two sets of optimized parameters for FDP model and FCP model, that is a total of four sets of parameters. Then the searched four sets of optimized parameters are substituted, respectively into two Grey Model Neural Networks of FDP model and

Table 2. Combination of two sets of optimized parameter for FDP and FCP.

Model	Parameter name	a	b1	b2	b3	b4	b5	b6
FDP	PSOGMNN	0.5972	0.4175	0.3955	0.6225	0.4704	0.5110	0.3707
	GAGMNN	0.6160	0.5033	0.6005	0.3660	0.5408	0.4797	0.3101
FCP	PSOGMNN	0.5548	0.5772	0.4980	0.5407	0.3292	0.6749	0.4627
	GAGMNN	0.6201	0.4118	0.6484	0.5608	0.4617	0.6003	0.5101

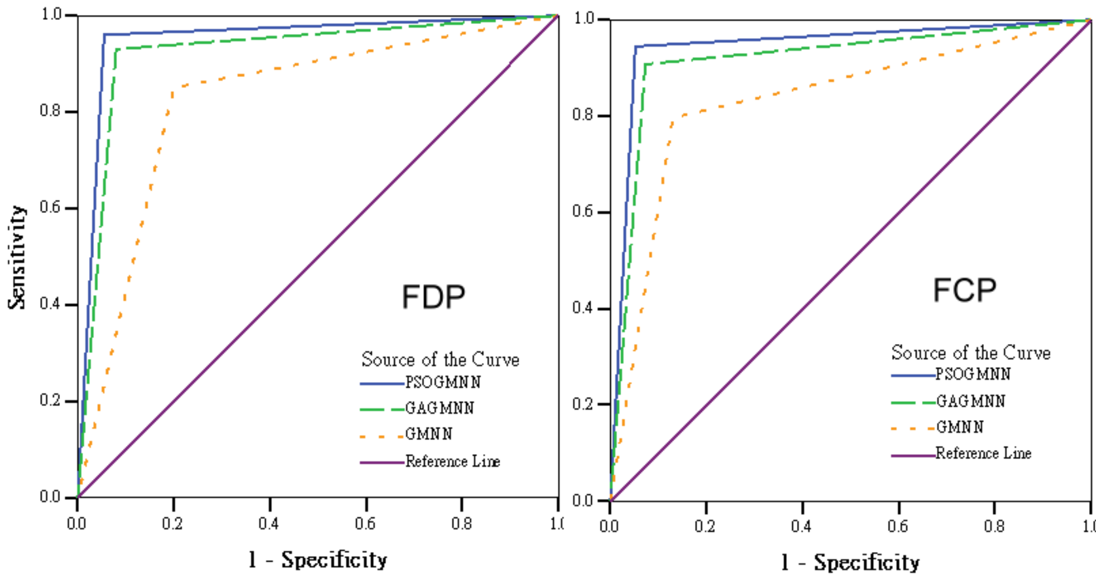

Figure 6. ROC curve of classification prediction result of financial distress prediction model and financial characteristic prediction model.

FCP model for model construction; finally, general Grey Model Neural Network is used to construct FDP model and FCP model. In the parameter setup of general Grey Model Neural Network, a, b1, b2, b3, b4, b5 and b6 are generated at random. As for the learning rate u1, u2, u3, u4, u5, u6, they are set up to be 0.0015.

General analysis on the classification prediction capability of FDP model and FCP model

Cross verification is done in a way that two small groups of data are used as training data to construct the model and one subgroup of data is used as test data to test model stability, and the results generated by three models of PSOGMNN, GAGMNN and general GMNN are used for plotting Receiver Operating Characteristic (ROC) curve, which is shown in Figure 6. Figure 5 is the classification prediction result of FDP model while the diagram on the right of Figure 5 is the classification prediction results of FCP model. Bradley (1997) pointed out that the larger the area on the reference line and below the curve, the more accurate the classification prediction capability of the model. From the figure, it can be clearly seen that no matter what it is the classification prediction result of FDP model or the classification prediction result of FCP model, PSOGMNN model usually shows the largest area underneath the curve; hence, it demonstrates the best classification capability. We then use Table 3 to observe the analytical output results of ROC curve, wherein sensitivity (Sen) means the percentage occupied by the number of results with prediction results of 1 (that is, company in crisis or company that is bad both at profit force and growth force) to the number of result with real value of 1; specificity (Spe) means the percentage occupied by the number of result with prediction result of 0 (that is, normal company or enterprise good at both profit force and growth force) to the number of result with real value of 0. Moreover, Hand (2001) pointed out that Gini Index = 2 × AUC – 1. When it comes to these index values, these values are the larger the better, as shown in Table 3. When FDP model adopts PSOGMNN model, the Spe is 0.960, Sen is 0.945, area under the curve (AUC) is 0.953 and Gini Index is 0.906. When FCP model adopts PSOGMNN model, the Spe is 0.944, Sen. is 0.948, AUC is 0.946 and Gini Index is 0.892, which are

Table 3. The analysis output result of ROC curve.

Set	Model	Sen	Spe	Auc	Gini
FDP	PSOGMNN	0.960	0.945	0.953	0.906
	GAGMNN	0.930	0.920	0.925	0.850
	GMNN	0.850	0.800	0.825	0.650
FCP	PSOGMNN	0.944	0.948	0.946	0.892
	GAGMNN	0.907	0.927	0.917	0.834
	GMNN	0.796	0.870	0.833	0.666

all higher than those of other models. Therefore, PSOGMNN model shows excellent classification prediction capability.

CONCLUSIONS AND SUGGESTIONS

The main contribution of the article is to propose newer PSO method to investigate the Financial Characteristic of many enterprises. Moreover, through the use of newer PSO Grey Model Neural Network parameter, the prediction capability is enhanced. In addition, it is also compared to the parameter of traditional Genetic Algorithm Grey Model Neural Network so as to investigate differences between the two and the classification prediction capability. The results of the research showcases that from Grey Relational Analysis, the enterprises of the first three rankings in profit force are CyberLink (5203), GT-Group (3085) and The Landis Hotel Taipei (5703); enterprises of the first three rankings in growth force are, respectively ChangHo (1468), JuhLien (5002) and TafFeta (1454). From PSO, it can be seen that one group is enterprises that are good at both profit force and growth force whereas the other group is enterprises bad at both profit force and growth force. Among classification prediction models, PSOGMNN has the fastest convergent RMSE, and its classification prediction accuracy is also higher than that of other models, which is worth the researchers' notice. In addition, PSO Grey Model Neural Network, Genetic Algorithm Grey Model Neural Network and general Grey Model Neural Network are used to perform the construction of FDP model and FCP model. In the future, it is recommended that PSO can be used to optimize other models (for example, Probabilistic Neural Networks (abbreviated as PNN) (Specht, 1990), Adaptive Neuro-Fuzzy Inference System (abbreviated as ANFIS) (Jang, 1993) to further investigate the construction and accuracy of FDP model and FCP model.

Abbreviations: PSO, Particle swarm optimization; **PSOGMNN,** particle swarm optimization grey model neural network; **GAGMNN,** genetic algorithm grey model neural network; **GMNN,** general grey model neural network; **FDP,** financial distress prediction; **FCP,** financial characteristic prediction; **SI,** swarm intelligences; **MAOS,** multiagent optimization system; **AGO,** accumulated generating operation; **FDP,** financial distress prediction; **FCP,** financial characteristic prediction; **RMSE,** root mean squared error; **ROC,** receiver operating characteristic; **AUC,** area under the curve.

REFERENCES

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.

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.

Holland J (1975). Adaptation in natural and artificial systems. University of Michigan Press. Ann Arbor, MI.

Jang JSR (1993). ANFIS: Adaptive-network-based fuzzy inference systems,IEEE Trans. Syst., Manage. Cybern., 23: 665-685.

Kuo YH, Huang ST (2007). The association of grey relational analysis and data envelopment analysis method to evaluate the enterprise performance of steel industry. 43rd annual meeting and 13th nationwide quality management forum of Chinese Society for Quality.

Li KL, Lin SC, Hsiao SH (2007). Performance index analysis of information service type supply chain model. Soochow J. Econ. Bus., 58: 61-88.

Liu CF, Lin WC, Su YL, Liu CP (2004). Using grey relational analysis to assess the business operation performance of irregular shipping companies in our country with stocks listed in the stock market. Shipp. Q. J. 13(4): 11-19.

Pan WT (2010). The use of genetic programming for the construction of a financial management model in an enterprise. Appl. Intell. (In Press).

Specht DF (1990). Probabilistic neural networks and the polynomial adaline as complementary techniques for classification. IEEE Trans. Neural Netw., 1(1): 111-121.

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

Yen JH, Wang SA (2005). Evaluation of operational performance for domestic financial holding companies using the entropy theory and grey relational analysis, third Management thinking and practice academic forum.