Groups Wisdom - 3D Fruit Fly Optimization Algorithm for Financial Distress Forecasting

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Abstract

In recent years, the global economic recession, followed by failure of business due to poor management, has resulted in a domino effect that occurred throughout the financial system. To avoid the expansion of loss, the issue of business failures should be seriously considered.

In this paper, firstly, to reduce the time and space spent in our models learning and prediction, we use the data mining methods -- stepwise regression, genetic algorithms and self-organizing map network for pre-processing data. Secondly, to match with the food searching behavior of the fruit fly, we modify Pan’s optimization algorithm to a three-dimension space for the General Regression Neural Network (FOAGRNN), then, compared it with the Backpropagation Neural Network, Genetic Programming, General Regression Neural Network (GRNN), and the traditional Least Square method for financial distress forecasting models. Finally, through a substantial number of experiments, we realized that if we wanted to study the company's financial crisis early warning, in addition to considering the company's financial variables, corporate governance variables should not be neglected. Besides, we also found that our modified 3D-FOAGRNN outperformed the General Regression Neural Network, Genetic Programming, Backpropagation Neural Network and the Least Square method in terms of forecasting accuracy.

Keywords: Data Mining, Fruit Fly Optimization Algorithm, General Regression Neural Network, Artificial Intelligence, ROC Curve, Financial Distress Models.

1. Preface

In recent years, the continuing inflow of foreign capital has caused Taiwan’s stock market to expand rapidly in size, and it is clear that Taiwan has already become one of Asia’s major capital markets. However, due to the maturity process, there have been plenty of potential crises and problems, including poor operation decision-making, high financial leverage, and the window dressing of the company’s financial statements, causing a higher than normal NPL ratio with-in the financial institutions. Although the negative impacts caused by the previously mentioned factors, often takes long time to surface. However, when economic recession or depression occurs, the industries might collapse due to operational failure, resulting in a domino effect that occurs throughout the financial system. In order to early detect and prevent any potential crisis that might occur, so the expansion of loss can be avoid, the business failure problems should be explored.

In the past, scholars used many early warning models in financial distress, but only a few papers concentrate the purpose on data mining for their inputs. Therefore in our paper, firstly, to reduce the time and space spent in models learning and prediction, we use the data mining methods -- stepwise regression, genetic algorithms and self-organizing map network for pre-processing data.

The main structure of this article is as follows: The first section we propose the data mining methods - Stepwise Regression, Genetic Algorithm and Self-organizing Map for pre-processing data. The second section will be an introduction of research methods including the Hybrid Fruit Fly Optimization Algorithm, General Regression Neural Network, Backpropagation Neural Network, and traditional regression analysis. Section 3 will be an introduction of our sample data and empirical results. The last section will be the research conclusion.

2. Research Method

2.1. Data Mining
It is only in the last decade, that the development and application of data mining in academic research starts to become popular. Its applications include marketing, finance, manufacture, health and so on. It was first traced back from Fayyad et al. (1996,1997). They thought that data mining is a series of steps for extracting knowledge from information, which makes the knowledge become efficient, brand new and potentially valuable. To consider the time and space spent in our learning and prediction process, we use the data mining methods - Stepwise Regression, Genetic Algorithms and Self-organizing Map network – to shrink-down a large number of the financial and economic variables, to some important variables for model inputs listed in Taiwan's companies. The above mentioned methods will be introduced as follows:

2.1.1 Genetic Algorithm

Genetic Algorithm, derivating from Darwin’s evolution point of view, was invented by John Holland (1975) and published in “Adaptation in Natural and Artificial Systems”. The evolution of gene can be used to find the best approximate solution more efficiently than other traditional econometrics methods and the characteristics of the finding processes are as follows:

1. When finding solution using the Genetic Algorithm, the problem’s possible answers or the parameters can be expressed through binary, integer, real numbers, or symbols. The Calculus-based optimization method has difficulties in processing non-differentiable and stochastic functions. However, the Genetic Algorithm can be used to solve the problems of such kind.

2. When Genetic Algorithm is finding the best solution, each time one Population is used, to search many possible answers with-in a large Solving Space. The size of the Population is considered based on the nature of the problem or the time cost, the bigger the number the Population it is consists of, the longer it will take to make the Population convergence.

3. When searching for the solution, it is highly possible that the Genetic Algorithm can only find the “Near Optimal Solution”, instead of the actual optimal solution. However, this “Near Optimal Solution” is already a decent solution, evolved from a very broad solving space, to a degree that best suits the target condition of certain type.

4. The Basic Genetic Algorithm calculations include Selection, Crossover, Mutation and other mechanisms. Those mechanisms are not fixed and they changes randomly according to demand, so even all the parameter settings are exactly the same each time, the calculation results might still vary slightly.

2.1.2 Stepwise Regression

If too many independent variables are used, when Stepwise Regression is solving a certain problem, the issue of “Collinearity” will be encountered. Therefore, how to find a few independent variables that can explain and predict the explained variable in a simpler manner, is a very critical subject in the field of statistics and econometrics.

Besides, Stepwise Regression can carry out filtering on many independent variables in the regression models, therefore reducing the time required in machine learning, when we construct a financial crisis in the future. The filtering is carried out in following steps: first, it does a test of significance of regression coefficients on the variables with the biggest partial correlation coefficient. This is done to decide if that variable should or should not enter the regression equation. Then it calculates the t value of every coefficient with-in the equation, to determine if it should remain in the regression equation. This process will be repeated till there is no coefficient being taken-in or removed.

2.1.3 Self-Organizing Map Neural Network

Self-Organizing Feature Map (SOM) was first introduced as an artificial neural network by Kohonen (1988). It is a type of neural network that is feedforward, unsupervised and competitive. This network imitates the brain nerve cell’s nature of having similar cells assembled in one same location. The network’s output processing units will influence each-other and after the network learning is finished, the ones near the output processing units will also have the similar functions. Because of the above, network learning can reach the objective of classifying the initially entered information through self-learning.

2.2. Artificial Intelligence

Artificial intelligence began in 1957, and it was not until 1980 that it starts to become popular. It did not require a lot of restricted assumptions of the multiple regression analysis, and could handle the qualitative variables and the different types of data. It is adaptive and has good learning capability and can tolerate errors. Many scholars used these methods to construct the early warning models in

Besides, in recent years the collective wisdom and bio-simulation algorithms that deal with the optimization problems are used gradually by many scholars, for example, Genetic Algorithm (Chtioui, Bertrand and Barba 1998), Ant Colony Optimization Algorithm (Dorigo and Gambardella 1997), Particle Swarm Optimization Algorithm (Srinivasan, Loo and Cheu 2003), Fruit Fly Optimization Algorithm (Pan 2012). In this paper, we not only modify Pan’s Fruit Fly Optimization Algorithm, but create a hybrid with Generalized Regression Neural Network (GRNN), Genetic Programming (Koza 1992, Sara 2007, Deng et al. 2013, Chen et al. 2013), back propagation network of Artificial Intelligence, as well as traditional least square method, to construct financial early-warning models, and also verify the differences of classification and prediction performance for these models.

2.2.1 Fly Optimization Algorithm
The Fruit Fly Optimization Algorithm (FOA) is a new method for finding global optimization. It is based on the food searching behavior of the fruit fly. Fruit flies have senses and perception better than other species, especially in smelling and vision (shown in Figure 1). The organ responsible for the sense of smell within fruit flies can search of all kinds of smells floating in the air, as well as smelling the food source that is 40 km away. Then, after it gets close to the food location, it can also use its sensitive vision to find food and the company’s flocking location, and fly toward that direction.

Pan’s Fruit Fly Optimization Algorithm (FOA) is a new evolution algorithm for finding food by randomizing characteristics. But its direction and distance are based on two dimensions only.

Figure 1. Illustration of the Group Iterative Food Searching of Fruit Fly

However, in our article we modify its judgment function based on three dimensions, by finding the food characteristics of the fruit fly. It is divided into necessary steps in the next sub-section:

2.2.2 Optimizing the GRNN by FOA
A General Regression Neural Network (GRNN) usually uses functional approaching method to solve the problem (Specht 1990, 1991). This article will hybrid the Fruit Fly Optimization Algorithm (FOA) to adjust the smoothing parameter (spread) value of General Regression Neural Network.

When spread value is small, and the radial basis function is relatively steep at the same time, it will make the weights vector neurons, that are closer to the input, to have an output that are bigger than other neurons. The network will react to the target vector that is the closest to the designed input vector; the more the spread value increases, the more glacis the slope of radial basis function will become, and many neurons can be reflected into the inputs vector. The action of the network is like to take the weighted mean within the target vector, and it’s designed input vector is closest to the new input
vector. Because of the above, when the spread value becomes bigger and bigger, more and more neurons will contribute into the average value, resulting in a more glacial network function.

In the FOAGRN model, this article adopted the MATLAB GRNN toolbox and the modified MATLAB program of Pan[19] in Figure 1. It has designed the spread parameter value of the FOA dynamic search of the optimized GRNN.

Our 3-D Fruit Fly Optimization Algorithm hybrids General Regression Neural Network (FOAGRN) and its parameter settings are illustrated as follow:

1. Random initial fruit fly swarm location:

   \[ X_{\text{axis}} = \text{rand}(); \ Y_{\text{axis}} = \text{rand}(); \ Z_{\text{axis}} = \text{rand}(); \]

   The number of iterations: \( \text{maxgen} = 100; \) population size: \( \text{sizepop} = 10 \)

2. Give the random direction and distance of drosophila \( i \) for the search of food by its olfactory.

   \[ X_i = X_{\text{axis}} + \text{Random Value} \]
   \[ Y_i = Y_{\text{axis}} + \text{Random Value} \]
   \[ Z_i = Z_{\text{axis}} + \text{Random Value} \]

3. In the beginning, we do not know the food’s position, therefore first estimate the distance with the origin (Dist), and then calculate the smell concentration value (S). This value is the reciprocal of the 3-D Dist.

   \[ \text{Dist}_{i} = \sqrt{X_{i}^{2} + Y_{i}^{2} + Z_{i}^{2}}; \quad S_{i} = 1/\text{Dist}_{i} \]

4. Substitute smell concentration value (S) for the spread (p) of GRNN neural network, \( p = S(i) \);

   Input the training and validation data, and get the output value (yc) of the grnn through the sim function,

   \[ \text{net} = \text{newgrnn}(\text{tr1}, \text{t1}, p); \]
   \[ \text{yc} = \text{sim}(\text{net}, \text{tr2}); \]

   Calculate the difference between the target output (t2) and the target output (yc). Then find Smell judgment function (RMSE or called Fitness function) with the target value(t2);

   \[ y = \text{yc} - t2; \%
   \]
   \[ \text{for ii=1:row1} \]
   \[ g = g + y(ii)^2; \]
   \[ \text{end} \]
   \[ \text{Smell}(i) = g^{0.5}/\text{row1}; \]

5. Determine the fruit fly with the maximum smell concentration among the fruit fly swarm (calculate the maximum value)

   \[ \text{[bestSmell bestIndex]} = \text{max(Smell)} \]

6. Retain the best smell concentration value and (x, y, z) coordinate, and at this moment, the fruit fly swarm will use vision to fly towards that location.

   \[ \text{Smellbest} = \text{bestSmell} \]
   \[ X_{\text{axis}} = X(\text{bestIndex}) \]
   \[ Y_{\text{axis}} = Y(\text{bestIndex}) \]
   \[ Z_{\text{axis}} = Z(\text{bestIndex}) \]

Enter into iterative optimization, repeat Steps 2-5, and determine whether the smell concentration is better than the previous iterative smell concentration, if yes, go to Step 6.
2.2.3 Classification Forecast Capabilities of All Models

Bradley(1997) pointed out that the larger the area under curve (AUC) of a model, the more accurate the model’s classification capacity. We see that sensitivity (Sen) refers to the percentage of actual 1s to predicted 1s (i.e. Dissatisfied), while specificity (Spe) refers to the percentage of actual 0s to predicted 0s (i.e. Satisfied); In other words, 1-Sen= type I error, 1-Spe= type II error. Professor Hand(2001) also pointed out that Gini Index = 2 × AUC – 1. Here, these index values are the larger the better.

In order to test the learning outcomes of the network, and to find its predictive ability of the financial crisis in advance, we adopt the ROC curve as an evaluation for the test network’s performance.

3. The Empirical Result

3.1. Research Variables and Scope

The source of 96 input variables used in this study, including the company information variables, financial variables, the corporate governance variables, the external rating variables and the macroeconomic variables are seasonal data gotten from Taiwan Economic Journal Database from 1995 to 2009. Meanwhile, each company in crisis is accompanied with two normal companies of the same nature, hence, with a deduction of enterprise with defective value, the total of 375 samples are collected.

These 96 variables include 57 financial variables (59.38%), respectively, ROA before Tax, Interest and Depreciation (x1), ROA before Interest and after Tax (x2), ROA before Interest and Depreciation and after Tax (x3), Return on Equity (x4), Return on Equity after Tax (x5), Gross Profit Margin (x6), Realize Gross Profit Margin (x7), Operating Profit Margin (x8), Net Profit Margin before Tax (x9), Net Profit Margin (x10), Non-operating Profit Margin (x11), Continuous Net Income Ratio after Tax (x12), Operating Expense Margin (x14), Cash Flow Ratio (x15), Debt Interest Rate (x16), Tax Rate (x17), Book Value Per Share(B) (x18), Book Value Per Share(A) (x19), Book Value Per Share(C) (x20), Continuous EPS (x21), Cash Flow Per Share (x22), Sales per Share (x23), Operation Profit Per Share (x24), Earnings Per Share before Tax (x25), Sales Growth Ratio (x26), Gross Profit Growth Ratio (x27), Realize Gross Profit Growth Ratio (x28), Operating Profit Growth Ratio (x29), Net Profit Growth Ratio before Tax (x30), Net Profit Growth Ratio After Tax (x31), Normal Net Profit Growth Ratio (x32), Continuous Net Profit Growth Ratio (x33), Total Asset Growth Ratio (x34), Equity Growth Ratio (x35), Depreciated Fixed Asset Growth Ratio (x36), Total Asset Return Growth Ratio (x37), Current Ratio (x38), Quick Ratio (x39), Interest Expense Ratio (x40), Debt/Equity Ratio (x41), Debts Ratio (x42), Equity/Asset Ratio (x43), Long-term Capital Ratio (x44), Degree of Dependence on Debt (x45), Contingent Debt/Equity Ratio (x46), Interest Cover (x47), Operation Income to Capital (x48), Pre-tax Income to Capital (x49), Inventory and AR to Equity (x50), Total Assets Turnover (x51), Account Receivable Turnover (x52), Inventory Turnover (x53), Fixed Assets Turnover (x54), Equity Turnover (x55), Net Operating Cycle (x56), Operating Revenue/Employee (x57), Operating Income/Employee (x58); 1 External rating variable(1.04%) – TCRI Credit Rating (x59); 2 Company Information Variables (2.08%) – Firm Years (x60) and Number of Employees (x13); 11 Macroeconomic Variables (11.46%), respectively, Unemployment Rate (x61), Taiwan Leading Indicators (x62), Taiwan Seasonal Nominal GNP (x63), Taiwan Real GDP (x64), Taiwan Monitoring Indicator (x65), Taiwan MIS Index (x66), Primary Loan Rate (x67), General Bank Loans Outstanding to Private Enterprises (x68), Discount Rate (x69), Rate of Change of Stock Indices (Monthly average) (x70), Rate of Change of Exports (x71); 25 Corporate Governance Variables (26.04%), including Numbers of Change of CPA for 3-years (x72), Directors and Supervisors Shareholding % (x73), Directors Shareholding % (x74), Supervisors Shareholding % (x75), Large Stockholder Shareholding % (x76), Managers Shareholding % (x77), Managers to Directors Ratio (x78), Directors and Managers (x79), Internal Managers (x80), Internal Supervisors (x81), Shares Pledged Ratio by Directors and Supervisors (x82), Shares Pledged Ratio by Directors (x83), Shares Pledged Ratio by Supervisors (x84), Directors and Supervisors Bonus to Pre-tax Profit % (x85), Directors and Supervisors Bonus (Millions) (x86), Employees Bonus to Pre-tax Profit % (x87), Related Party Sales % (x88), Receivables Related Parties/Equity (x89), Property Transaction Loss or Gain % from Related Parties (x90), Numbers of Changing Financial Forecast (x91), Numbers of Changing
3.2. Data Pre-Processing

First, from the 96 variables that are already collected, we filter out 14 variables using Stepwise Regression Analysis \(^1\), then filter out 30 variables using Genetic Algorithm \(^2\). Among those filtered out variables, there are five of them that are overlapping \(^3\): Those 5 variables are Tax Ratio, Debts Ratio, Long-term Capital Ratio, Shares Pledged Ratio by Directors and Supervisors, and Directors and Supervisors Bonus to Pre-tax Profit %. Through empirical results in this paper, we realized that if we want to study the company's financial crisis early warning, in addition to considering the company's financial variables, corporate governance variables should not be neglected.

Use the above three groups of variables, through the SOM’s 3x3 major kinds of clustering method, after 500 times of learning; we can aggregate out the groups of normal and default companies. Among the largest category, there are composed of 84 normal companies and 12 crisis companies based on 5 variables; 84 normal companies and 10 crisis companies based on 14 variables; 114 normal companies and 25 crisis companies based on 30 variables. The above 3 types of variables, after re-categorization has 55 normal companies and 5 crisis companies, they were located in 18 different industries. Furthermore, through the industry ranking, there are approximately 40 companies, with-in the repeated sampled 55 normal companies, that has Earnings Per Share before Tax (dollars) ranks at 33.33% and below, the ratio of having those companies located in one certain industry is approximately 72.72% (40/55).

In conclusion, by the SOM method, we can determine that the fairly small variables can still aggregate out the groups of normal and default companies. And through the industrial structure analysis, we can learn more about the degree of aggregation in the company and its operating status.

3.3. Performance comparison between traditional regression and AI models

3.3.1 Prediction accuracy

In this article, 375 sample data are normalized to make variables in the range from 0 to 1. It is then divided all sample data equally into five groups with each contains 75 data rows. Four groups of data are used as training and validation data, and one group of data used as test data to test the model stability. Training and validation data of four groups are used to construct the models of FOAGRNN, GRNN, Genetic Programming, Back-propagation Neural Network, and traditional Multiple Regression, respectively.

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\(^1\) Stepwise regression selected 14 variables: 5 financial variables (x1, x2, x17, x42, x44), 1 external variable (x59), 8 corporate governance variables (x72, x77, x81, x82, x85, x89, x90, x91).

\(^2\) Genetic algorithm selected 30 variables: 20 financial variables (x12, x13, x17, x19, x21, x26, x28, x29, x32, x33, x34, x35, x38, x42, x44, x47, x51, x52, x55, x56), 2 macroeconomic variables (x67, x69), 8 corporate governance variables (x73, x74, x76, x82, x85, x87, x94, x96).

\(^3\) Among those filtered out variables, there are five of them that are overlapping: 3 financial variables (x17,x42,x44), 2 corporate governance variables (x82,x85)
Regarding GP, GRNN literatures, the readers can refer to the related publications of professors [6,14,15,21,22,23,24]. In the FOAGRNN model, this article has adopted the MATLAB GRNN toolbox and self-written modified FOA program. It has also designed the spread value of the FOA dynamic search of optimized GRNN. The initial value of the spread of GRNN is set up in the range of [0.01, 1], and the neuron number of the network input layer is 5, and the output neuron number is one. The best smell concentration judgment value (S) is kept to be used as the spread value of GRNN, and the iterative search is made based on this method. Through the smell of the fruit fly’s random food finding, and through the flocking at the location of the highest concentration of smell using vision, the spread value of GRNN can be adjusted to its optimal value, and the RMSE between network output value and target value can be adjusted to the minimal value.

<table>
<thead>
<tr>
<th>Items</th>
<th>Artificial Intelligent Models</th>
<th>Regression Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Models</td>
<td>FOAGRNN</td>
<td>GRNN</td>
</tr>
<tr>
<td>Accuracy(%)</td>
<td>86.7</td>
<td>82.9</td>
</tr>
</tbody>
</table>

![Figure 2. Classification Prediction Capability of AI and Regression](image)

From the Table 1, it can be clearly seen that the FOAGRNN model has the best average prediction accuracy (20 Runs) based on outside sample (75 observations), and keeps stably at 86.7%. Next are GRNN(82.9%), GP(80.9%) and BP(80.3%) respectively. All the empirical results are shown in Figure 3-5. In other words, it shows that the network learning of artificial intelligent has positive effect on performance of prediction. And the average prediction accuracy performance (82.7%) of artificial intelligent models is better than that of traditional regression model (78.7%).

### 3.3.2 ROC curve analysis

The output result of all models is defined as when it is smaller than or equal to 0.5, it is classified as 0 (that is, it is normal company); when it is larger than 0.5, it is classified as 1 (that is, company in risk). To observe the predictive ability of all models and they are drawn into the ROC curves diagram.

From the Figure 2, it can be clearly seen that the modified FOAGRNN (FOA) model has the best classification capability. Then, from an observation of the ROC curve analysis results in Table 2, for
FOAGRNN, Sen is 0.76, Spe is 0.920, Area under the curve (AUC) is 0.84, and Gini Index is 0.68, which are all higher than those of the GRNN and GP, BP and traditional Regression model. Therefore, the modified FOAGRNN model has a very decent classification prediction capability. In addition, we only list one of the 20 tests, Sara Silva’s GP optimal strategy, as follow:

\[ \cos(\text{plus}(\sin(\text{minus}(X2,X5)),\sin(\text{times}(\text{plus}(X2,\text{times}(\text{plus}(\text{plus}(\text{minus}(\sin(X2),X5),\sin(X2)),X4),X2)),X2)))) \]

<table>
<thead>
<tr>
<th>Items</th>
<th>Methods</th>
<th>Gini</th>
<th>AUC</th>
<th>Standard Deviation</th>
<th>Sen</th>
<th>Spe</th>
<th>(Sen+Spe)/2</th>
<th>P-Value</th>
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</thead>
<tbody>
<tr>
<td>Artificial Intelligence</td>
<td>FOAGRNN</td>
<td>0.680</td>
<td>0.840</td>
<td>0.12</td>
<td>0.760</td>
<td>0.920</td>
<td>0.840</td>
<td>0.000</td>
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<td></td>
<td>GRNN</td>
<td>0.522</td>
<td>0.761</td>
<td>0.15</td>
<td>0.558</td>
<td>0.964</td>
<td>0.761</td>
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<tr>
<td></td>
<td>GP</td>
<td>0.533</td>
<td>0.767</td>
<td>0.14</td>
<td>0.64</td>
<td>0.893</td>
<td>0.7665</td>
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<tr>
<td></td>
<td>BP</td>
<td>0.465</td>
<td>0.733</td>
<td>0.15</td>
<td>0.52</td>
<td>0.945</td>
<td>0.7325</td>
<td>0.000</td>
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<tr>
<td>Econometrics</td>
<td>OLS</td>
<td>0.46</td>
<td>0.730</td>
<td>0.15</td>
<td>0.56</td>
<td>0.90</td>
<td>0.73</td>
<td>0.000</td>
</tr>
</tbody>
</table>

And the all empirical processes of our Matlab programs are shown in Figure 3-5, respectively. 8 results of processes of GP are (a) Fitness, (b) Population Diversity, (c) Structural Complexity, (d) Genetic Operators, (e) Desired and Obtained, (f) Accuracy vs. Complexity, (g) Pareto Front and (h) Tree Structure in Figure 3 below. The process of BP is shown in Figure 4, and four processes of FOAGRNN are also shown as (a) RMSE of iterative Search, (b) 3-D Search Route, (c) Spread best of FOAGRNN and (d) Distance of Iterative Search in Figure 5, respectively.
Desired and Obtained

Accuracy vs. Complexity

Pareto Front

Tree Structure

Figure 3. Illustration of the all Processes of GP

Figure 4. Illustration of the Process of BP
4. Conclusion

The main contribution of this article is as follows: First, this study indeed improves the learning efficiency of applying the data mining—Stepwise Regression, Genetic Algorithm and Self-organizing Map for pre-processing data. Through a substantial number of experiments, we realized that if we wanted to study the company's financial crisis early warning, in addition to considering the company's financial variables, corporate governance variables should not be neglected. Secondly, we modified Pan’s FOA algorithm to three dimensions to make searching food path of the fruit fly more flexible and efficient. This article also uses modified FOAGRNN, Genetic Programming, Back Propagation Network and Generalized Regression Neural Network as well as traditional regression model to construct financial early-warning models.

From the empirical result, it can be seen that through applying the modified FOA optimized GRNN network, the predictive ability of GRNN can be significantly enhanced. Using all models with-in this paper to construct the early warning system also can effectively reduce the misjudgment rate of enterprise crisis diagnosis. In addition, the performances of all early warning models constructed by AI learning methods are better than that of traditional regression model.

5. References