An Empirical Study of Dynamic Financial Early Warning Based on Grey Correlation and BP Neural Network

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Abstract

Current research on early warning of financial crises mainly focuses on financial early warning such as multivariate linear pre-warning and Bayes discrimination, whereas the research methods are inclined to mathematical statistics, so there are rigorous requirements for data and hypotheses. Nevertheless, corporate financial risks and predetermined indices for early warnings are possibly changeable. In consideration of ineffective control of crises by earning warning, crises were dynamically monitored with a BP neural network based on Grey Model (1, 1) from the perspective of risk and crisis forecast (the only measures available for financial crisis in modern enterprises). Besides, a three-tier BP neural network was constructed by transforming fitting accuracy of exponential functions. The results have suggested that the changing indices about corporate financial crises have direct impacts upon corresponding early warning results. All simulation trainings based on BP neural network have been validated and can be used to further verify dynamic grey correlations in the process of financial early warning. Furthermore, all ST enterprises were predicted to face crisis by the pre-warning mechanism based on grey model, BP neural network training and the analog control, while corresponding non-ST enterprises were forecasted to be sound. Hence, it is helpful for listed enterprises to effectively forecast their possible and potential financial crises.

Keywords: Financial Early Warning, BP Neural Network, grey model, Grey Model (1, 1)

1 Introduction

As the globalization of economy is constantly deepened and the competition becomes increasingly fierce among enterprises, plenty of new problems have occurred to financial management of enterprises. In particular, there have been new requirements for corporate financial management, especially the early warning of financial crises in routine operation of small and medium-sized enterprises which are bankrupt or reorganized for competition. Meanwhile, the measures for handling crises have changed to different extent. Particularly, corresponding financial risks would potentially increase in case of any changes to indices of modern enterprises.

2 Theoretical Review

Concerning the application of tools for forecasting financial tools, Lyn C. Thomas considered that corporate financial crises rapidly increased with frequent use of financial tools. Besides, he advocated further validation and analysis should be undertaken by embedding stakeholders' behavioral models, so as to clarify causes of corporate financial crises and crises transmission channels, etc.

In combination with a rough set, Pratap, A., Agarwal, S., and Meyarivan, T made up the deficiencies of existing research on data mining for processing noises in predicting financial crises. In addition, they proposed that it was feasible for the improved self-adaptive genetic algorithm to forecast financial crises of listed enterprises based on genetic algorithms.

As regards the forecast of financial crises, Yudong Zhang and Lenan Wu upheld that, to increase the accuracy of a BP neural network model for predicting chaotic time sequences, it was necessary to optimize its prediction methods based on genetic algorithms and improve the determination of weight and threshold value by the training of BP neural network, for the purpose of optimizing the training effect of this network. Mingzhi Mao and EE.C. Chirwa deemed that GM (1, 1) had remarkable index characteristics, required a relatively small amount of samples and could predict with relatively high accuracy. Besides, they highlighted that the original data of samples should be further adjusted to improve estimation accuracy when GM (1, 1) was applied. Chih-Fong Tsai and Yu-Chieh Hsiao established a model for forecasting the development trends of enterprises in stock market in combination with BP neural network, simulating and predicting the trends with multiple methods of BP neural network like batch learning according to indices such as net earnings and profits per share. The results showed that BP neural network was somewhat valuable for predicting the development tendency of stock market.

3 Construction of an Early Warning Model for Financial Crises

3.1 SELECTION OF INDICES AND SUB-INDICES OF FINANCIAL CRISES

It may be known from above analysis that importance shall be attached to practices in terms of corporate financial risks

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and early warning, so it is critically important to properly select indices on financial risks and crises according to practical situation of enterprises. Based on current development of Chinese listed enterprises, this paper examined if ST (Special Treatment) was used as a criteria for discriminating corporate financial crisis. According to existing research, indices were defined for corporate financial crises by various methods. In this paper, 19 sub-indices were examined and studied altogether, including cash flow, asset structure, corporate business performances, profitability and space for growth, as shown in Table 1 as follows.

Above 19 sub-indices were selected based on a T-test to make sure if effective early warning was available for financial crisis and further discriminated according to significant differences of variables between ST and non-ST enterprises. To further clarify the intervention of selected indices in early warning of corporate financial crises, possible correlations between the indices were explored through T-tests. For this purpose, the error-correction model was simplified by high coincident and multicolinear indices by considering 0.7 as the critical value for discriminating multicolinearity of above indices. Then, an early warning model was constructed for corporate financial crises according to aforementioned research objectives from the perspective of earnings per share, net asset value per share, cash flow per share and flow rate.

3.2 SELECTION OF SAMPLES

To make sure that the samples were sufficient for the research, they were selected according to financial operations of ST and non-ST listed enterprises, mainly including samples for modeling and early warning. The former samples primarily referred to training sources of BP neural network in this research framework and they were selected to make models practically effective for early warning. The former samples were selected to improve their prediction performances to evaluate if they were reasonable or not. In consideration of matching the quantity of the sample data, ST and non-ST enterprises were chosen at an equivalent proportion according to different financial conditions and factors of enterprises from different industries, so as to obtain further empirical evidences.

4 Models for Corporate Financial Crises

4.1 MODEL SELECTION AND MODELING

In view that there was only a limited amount of ST and non-ST listed enterprises that could be used as samples, GM (1, 1) was applied on the grounds that relatively high estimation precision should be ensured on the premise of small sample size. The basic model is shown as follows:

$$x^{(0)} = a^{-y^{(0)}} = \left(a^{-y^{(0)}(1)}, a^{-y^{(0)}(2)}, \ a^{-y^{(0)}(3)}, \ldots a^{-y^{(0)}(n)}\right)(a \geq 1)(x^{(0)}(1) \geq e) \tag{1}$$

Based on above analysis, the linear differential equation of the integrated first-order model for predicting grey correlations was determined as:

$$\frac{d_x^{(1)}}{d_t} + ax = u \tag{2}$$

Where the coefficients and parameters of the above formula were dependent upon undetermined coefficients (a and u). Then, a new matrix was estimated as follows by built-up method, namely $x^{(0)}(k) \to x^{(1)}(k)$:

$$B = \begin{bmatrix} -[x^{(1)}(1) + x^{(1)}(2)]/2 & 1 \\ -[x^{(1)}(2) + x^{(1)}(3)]/2 & 1 \\ -[x^{(1)}(3) + x^{(1)}(4)]/2 & 1 \\ \vdots & \vdots \\ -[x^{(1)}(n-1) + x^{(1)}(n)]/2 & 1 \end{bmatrix} \tag{3}$$

Thus, a model of dependent variables was obtained as follows:

$$Y = [x^{(0)}(2) \quad x^{(0)}(3) \quad \cdots \quad x^{(0)}(n)]^T \tag{4}$$

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \tag{5}$$

Where the original sequence of Formula (5) is $x^{(0)}(k)(k = 1, 2, 3, \ldots n)$. In combination with Formula (3), Formula (5) may be converted into:

$$\hat{a} = \begin{vmatrix} a \\ u \end{vmatrix} = (B^T B)^{-1} B^T Y \tag{6}$$

After determining aforementioned undetermined coefficients, corresponding differential equation [Formula (1)] may be solved. The model of pertinent time sequence $\hat{x}(t)$ and its cumulative time sequence for forecasting grey correlations was obtained as follows:

$$x^{(1)}(t) = (x^{(1)}(1) - \frac{u}{a})e^{-at} + \frac{u}{a} \tag{7}$$

According to above results, Formula (5) was converted through cumulative deduction into following model for predicting financial crises:

$$\hat{x}^{(0)}(t+1) = \alpha^{(1)} \hat{x}^{(1)}(t+1) = Ae^{-at} \tag{8}$$

Corresponding solution is:

$$A = (x^{(1)}(0) - \frac{u}{a})(1 - e^a) \tag{9}$$

Besides, the accuracy of relative errors, residual values, average relative errors and mean precision, etc was tested to make sure reliable application of models.

4.2 CORRECTING FITTING ACCURACY OF SAMPLES

The data accuracy shall be also taken into account after modeling. It may be known from existing trigonometric functions and changes of exponents with functions, etc that none of the models may completely interpret indices while considering their precision. The data of models were further processed by exploring the exponential functions that are transformed from negative to positive values from the perspective of low operability and prediction precision of original sample data. Assuming $x^{(0)}$ of Formula (8) as the sequence for constructing GM (1, 1), then the $1-AGO$ sequence is $x^{(1)}$. In this way, an overall mean sequence could be established based on x^0 and x^1 as follows.

$$z^{(1)}(k)=\frac{1}{2}(x^{(1)}(k)+x^{(1)}(k-1)) \tag{10}$$

According to defined GM (1, 1), the grey differential equation was obtained as follows:

$$x^{(0)}(k)+az^{(1)}(k)=b \tag{11}$$

The above formula could be converted into following formula after winterization:

$$\frac{dx^{(1)}(t)}{dt}+ax^{(1)}(t)=b \tag{12}$$

In combination with Formulas (8) and (11), the GM (1, 1) model with basic framework was obtained:

$$\hat{x}^{(1)}(k+1)=\left(x^{(0)}(1)-\frac{b}{a}\right)\bullet e^{-ak}+\frac{b}{a} \tag{13}$$

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k)$$

After least squares estimation (LSE) of Formula (13), the following formula was obtained:

$[a \quad b]^T=(B^TB)^{-1}B^TY$, where the transposable matrix was $B=\begin{bmatrix}-z^{(1)}(2) & 1\\ -z^{(1)}(3) & 1\\ \vdots & \vdots\\ -z^{(1)}(n) & 1\end{bmatrix}$.

Then, the matrix of transversal vectors constructed according to dependent variables could be transposed into following matrix:

$$Y=\left[x^{(0)}(2),\quad x^{(0)}(3),\quad \cdots \quad x^{(0)}(n)\right]^T \tag{14}$$

4.3 NEURAL NETWORK MODELS

For listed enterprises' financial early warning based on grey models, it is necessary to further validate if these enterprises will suffer financial crises that are discriminated with models and control corporate subsequent financial affairs based on corresponding early warning models. In controlling listed enterprises' financial risks and crises by early warning, the correlations between early warning signals and financial situation need to be considered while concentrating on if risks will occurs or not. In view of possible non-linear mapping between early warning signals and financial situation, BP neural network was finally used to verify the mapping between above financial crisis early warning and listed-enterprises financial affairs. In consideration that increasing tiers of BP neural network is harmful for the prediction precision of this network and unipolar BP neural network is unfavorable for forecasting sample functions of continuous intervals, a three-tier BP neural network was selected as the final correction model. According to above analysis, some redundant values were selected from the initial crisis indices to compose a rough input tier of BP neural network. Next, the number of nodes was increased in the hidden tier of the BP neural network, for the purpose of self-adaptive learning of evaluation and early warning on the network after grey fuzzy evaluation as mentioned above. Subsequently, the outcomes of learning neural network and corresponding quantitative outputs of level-5 early warning were obtained according to above results of grey fuzzing evaluation. In setting the warning signals transformed from early warning of corporate financial crises, namely in determining the output state of the rough BP neural network during learning this network, level 1 to level 5 risks formed warning-free signals, generally warned signals, moderately warned signals and seriously warned signals respectively. Meanwhile, 60 middle node tiers and 5 input tiers were selected to compose a multi-tier BP neural network by considering indices of corporate financial early warning that had been reduced by the above grey fuzzy model as the tier for inputting nodes. Reduced evaluation indices for early warning of risks were initialized through the learning and extrapolation on BP neural network by setting upper error limit, learning rate and inertial parameters. The data within an interval were introduced into the rough BP network after processing to be further learnt and trained. Then, a neural network with multiple tiers of nodes was obtained for calculating and optimizing assignments. In this way, the learning and reasoning results on early warning were gained from the grey fuzzy framework for evaluating corporate financial early warning through the neural network.

5 Empirical Analysis

5.1 ON BP NEURAL NETWORK OF EARLY WARNING OF CORPORATE FINANCIAL CRISES

To further examine the effectiveness for early warning of financial crises by integrating grey correlation with BP neural network, ST and non-ST enterprises were selected at an equivalent proportion (1:1) to construct a training module for BP neural network based on four categories of basic financial indices. Besides, BP neural training was conducted for simulating early warning based on the data of financial early warning. Tables 2 and 3 respectively report the neural network training results for financial early warning of ST and non-ST enterprises.

From Tables 2 and 3, it may be observed that the BP neural network selected in this paper is feasible for analyzing the prediction results of grey models since it has passed all simulative trainings on financial early warning. Grey dynamic correlations of corporate financial affairs are forecasted by selecting five ST and five non-ST listed enterprises as samples to be preliminarily warned by grey correlation and BP neural network training.

5.2 ON PREDICTION RESULTS OF DYNAMIC FINANCIAL EARLY WARNING MODEL BASED ON GREY CORRELATION AND BP NEURAL NETWORK

As shown in the following table, all ST enterprises are pre-warned to be in crisis, while all of the corresponding non-ST enterprises are predicted to be sound, so grey correlation and BP neural network proposed in this paper are effective for early warning of corporate financial risks.

6 Conclusion

In this paper, GM (1, 1) requiring sample size with relatively high estimation precision was selected based on risk and crisis forecast (the only measures available for coping with financial crises in modern enterprises) and ineffective control of early warning over crises. Meanwhile, the data of models were further processed according to the exponential functions that had been transformed from negative to positive values, so as to make sure that the GM (1, 1) is fairly effective for early warning of corporate financial crises. In addition, non-linear mapping was achieved on the BP neural network based on the probability of GM (1, 1)-based early warning of financial crises. The conclusions are specifically reached as follows.

Firstly, various indices of listed enterprises impose intricate impacts upon their financial crises. In particular, they will be affected accordingly once financial crises preliminarily warned by models occur, because the cash flow, asset structure, corporate business performance, profitability and space for growth as mentioned above are highly correlated causes of corporate financial crises. Therefore, it is important for listed enterprises to solve financial crises by rigorously controlling their financial affairs from the above perspectives.

Secondly, it is helpful for listed enterprises to effectively forecast their possible and potential financial crises by examining early warning and prevention of such crises by grey models (early warning mechanisms) constructed in this paper and BP neural network training. The effects of early warning are dependent upon corporate proper establishment of pertinent property monitoring measures and index frameworks. Hence, enterprises need to construct monitoring systems for financial crises that are suitable for their own growth according to their development characteristics.

Thirdly, without being limited by early warning or warning of financial crises as existing studies, this paper has established non-linear relationships between indices and actual crises by integrating GM (1, 1) with BP neural network to give pertinent dynamic early warnings of listed enterprises' financial risks.

References

[1] CF Tsai, YC Hsiao 2010 "Combining multiple feature selection methods for stock prediction: Union, intersection, and multi-intersection approaches," *Decision Support Systems* **50** (1), 258-269.
[2] Clerc, M., & Kennedy, J. 2002 "The particle swarm: Explosion, stability, and convergence in a multi-dimensional complex space," *IEEE Transactions on Evolutionary Computation* **6**, 58-73.
[3] CY Kung, KL Wen 2007 Applying Grey Relational Analysis and Grey Decision-Making to evaluate the relationship between company attributes and its financial performance - A case study of venture capital enterprises in Taiwan *Decision Support Systems* **43**(3) 842-852
[4] Guthrie, R Neumann 2007 Economic and non-financial performance indicators in universities: The establishment of a performance-driven system for Australian higher education *Public Management Review* **9**(2) 231-252
[5] *Deleted by CMNT Editor*
[6] J Kennedy 2010 "Particle swarm optimization," *Encyclopedia of Machine Learning*, 760-766.
[7] K Deb, A Pratap, S Agarwal 2002 "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions*, 182-197.
[8] LC Thomas 2000 "A survey of credit and behavioural scoring: forecasting financial risk of lending to consumers," *International Journal of Forecasting* **16** (2), 149-172.
[9] M Bussière, M Fratzscher 2006 "Towards a new early warning system of financial crises," *journal of International Money and Finance* **25** (6), 953-973.
[10] M Mao, EC Chirwa 2006 "Application of grey model GM(1, 1) to vehicle fatality risk estimation," *Technological Forecasting and Social Change* **73** (5), 588-605.
[11] *Deleted by CMNT Editor*
[12] T Mitton 2002 "A cross-firm analysis of the impact of corporate governance on the East Asian financial crisis," *Journal of financial economics* **64**(2),215–241.
[13] V Bosilj-Vukšic 2008 "The impact of business process orientation on financial and non-financial performance," *Business Process* **4**(15), 738-754.
[14] V Ivashina, D Scharfstein 2010 "Bank lending during the financial crisis of 2008"*Journal of Financial economics* **97**(3), 319-338.
[15] Y Zhang, L Wu 2009 "Stock market prediction of S&P 500 via combination of improved BCO approach and BP neural network," *Expert systems with applications* **36**(5), 8849-8854

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