Applied Mathematics and Computation 251 (2015) 431–441

Contents lists available at ScienceDirect

Applied Mathematics and Computation

journal homepage: www.elsevier.com/locate/amc

A hybrid approach using two-level DEA for financial failure prediction and integrated SE-DEA and GCA for indicators selection

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ARTICLE INFO

Keywords:
Two-level DEA
Super-efficiency DEA
Grey relational analysis
Financial failure prediction
Indicators selection

ABSTRACT

Corporate financial failure prediction is playing an increasingly important role for both shareholders and companies. There are many different approaches that have been developed over the years. The aim of this paper is to introduce a new data envelopment analysis (DEA) model that is a two-level DEA as a quick and feasible tool for corporate financial failure prediction, which is able to handle quite a large number of inputs and outputs by utilizing hierarchical structures of financial indicators. To use the two-level DEA model, we need to select high relevant indicators from a large set of candidate indicators as inputs and outputs, which is not trivial. So the approach that integrates the super-efficiency DEA (SE-DEA) and the grey relational analysis (GRA) is introduced to select financial indicators that have more meaningful correlations with the corporate financial situation from a lot of indicators. The results of empirical analysis conducted on companies listed in Shenzhen Stock Exchange Market (SSEM) of China demonstrate the advantage of the two-level DEA and the integrated SE-DEA and GCA over the CCR and the BCC.

1. Introduction

Because of the radical change in global economy, corporate financial failure prediction plays an increasingly important role. Financial failure often occurs when a firm has chronic and serious losses and/or when the firm becomes insolvent with liabilities that are disproportionate to assets [1]. Widely identified causes and symptoms of financial failure include poor management, autocratic leadership, and difficulties in operating successfully in the market. Corporate bankruptcy causes substantial losses to not only the business community, but also the society as a whole. Therefore, accurate financial failure prediction models are of critical importance to various stakeholders, i.e., management, investors, employees, shareholders, and other interested parties, as the models provide them with timely warnings.

There are various financial failure prediction models in the related literature. Early studies on financial failure prediction employ univariate approaches using ratio analysis [2]. Later on, multivariate approaches that combine multiple ratios and characteristics such as the linear multiple discriminant approach [3], the multiple regression [4], and the logistic regression [5] are used to predict potential financial failures. More recently, artificial intelligence and machine learning techniques such as neural network, genetic algorithm, decision trees, case-based reasoning, expert systems, and support vector machines are

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http://dx.doi.org/10.1016/j.amc.2014.11.077

widely used in corporate financial failure prediction because of its universal approximation property and the ability of extracting useful knowledge from vast data and domain experts [6].

Data envelopment analysis (DEA) is introduced to determine the relative efficiency of a set of similar decision making units (DMUs), where each DMU uses multiple inputs to produce a number of outputs [7]. DEA is able to provide measures for the efficiency of a corporation [8], thus DEA is employed as a tool to predict corporate failure in many studies [9]. For example, Cielen et al. [10] apply DEA for financial failure assessment and compare DEA with mathematical programming based discriminant analysis methods. Premachandra et al. [11] propose a DEA model to predict bankruptcy and compare their results with the logistic approach to show that the DEA model could be effectively used in predicting corporate failure. Sueyoshi and Goto [12] discuss the methodological strength and weakness of DEA and DEA–DA from the corporate failure perspective. Shetty et al. [13] modify the directional distance formulation of DEA that can locate the worst performing DMU and determine an inefficient frontier for financial failure early warning.

In the previous bankruptcy assessment, one-level DEA models or some improved one-level DEA models are used in many researches. One-level DEA is limited in financial failure assessment because the discrimination power of DEA will be weakened if too many input or output indicators are used [1]. In bankruptcy assessment, a dozen of financial indicators are usually used in order to evaluate corporate condition comprehensively, such as Ryu and Yue [14] use 70 indicators; Gestel et al. [1] use 45 indicators. Moreover, some of the financial ratios that we deal with in financial failure prediction have many similar characteristics and the similarity between indicators may also weaken the discrimination power of DEA [15]. Meng et al. [16] propose a two-level DEA model to deal with systems with a large number of inputs and outputs that share the same characteristics. The two-level DEA approach arranges the inputs and outputs in two hierarchy levels by categorizing them into separate groups according to the similarity, for which the indicators assigned to the second level are considered as subindices to those in level one.

Meng et al. [16] use the two-level DEA approach to evaluate the efficiency of 15 institutes for basic research in the Chinese Academy of Sciences. Kao [15] extends the analysis of Meng et al. [16] and proposes an alternative linear model that is easier to handle. The two-level model constructed from the primal and dual forms of the conventional one-level DEA model has a kind of dual relationship [15], so it has all the advantages that those one-level DEA models have. Zhiani and Davoodi [17] show that the two-level DEA model is a special case of the DEA models for which weight restrictions are applied. So the two-level DEA model is an efficient approach to deal with systems with a large number of inputs and outputs that share the same characteristics and thus can be grouped into several categories [16]. It is also a suitable approach with a stronger discrimination power than that of the conventional one-level model because the former has more stringent constraints on the multiplier. To the best of our knowledge, the two-level DEA model, however, has not been used in financial failure prediction so far.

Feature selection is defined as a process of selecting relevant features out of a large set of candidate features. The motivation of feature selection is to reduce the dimensionality of the feature space, reduce the cost of the computation, and improve the prediction accuracy. As mentioned above, because financial indicators are usually used in dozens to evaluate the corporate financial condition comprehensively, various methods for feature selection are used in financial failure prediction, such as statistical methods [18], genetic algorithm [19], rough set theory [20], random forests [21], etc. grey relational is the uncertainty associated with things or uncertainty associated with system factors and main behavioral factors [22]. Grey relational analysis (GRA) is used to study the key indicators in system models to help in prediction and decision making. If the change trend of the two factors is basically the same or closely related, then it means that the grey relational degree is higher [23]. The GRA is used to determine the relevant and key indicators that affect the characteristics of a system in many studies, e.g., Li [24] and Jia [25]. The GRA is, however, rarely used in financial failure prediction.

Super-efficiency DEA (SE-DEA) is a method to rank the performance of efficient DMUs [26]. SE-DEA excludes the DMU under evaluation from the reference set so that efficient DMUs may have efficiency scores bigger than or equal to 1. SE-DEA also helps in generating more meaningful correlations and measures of central tendency in an empirical application with multiple efficient units, for which such units would otherwise share the same score of 1 [27]. Banker and Chang [28] demonstrate that the use of the super-efficiency model for ranking efficient DMUs is appropriate. Recently, SE-DEA is used in the selection of indicators and to evaluate the relative efficiency. For example, Avkiran [27] uses the SE-DEA to identify the key financial ratios so as to help ratio analysis.

In this paper, we propose a hybrid financial failure prediction approach that uses a two-level DEA integrating the SE-DEA and the GRA methods for indicators selection. We first introduce a new method that combines the SE-DEA and the GRA to select financial indicators that have more meaningful correlations with the corporate financial situation from a lot of indicators. This new approach is novel in the sense that, unlike the traditional GRA, our method uses the SE-DEA model to determine the optimal weights for each indicator of each company. Then, the grey relational degrees of the financial indicators with financial situation can be calculated. Moreover, we use a two-level DEA model to analyze the efficiency values of the companies listed in China Shenzhen Stock Exchange Market with the multi-level financial indicators and compare with the efficiency values calculated by some other DEA models.

The rest of this paper is organized as follows. The next section is devoted to a hybrid method based on the SE-DEA and the GRA for financial indicators selection. In Section 3, we describe the two-level DEA model for financial failure prediction. In Section 4, we present the experimental results of the proposed method. Finally, we conclude the paper and discuss future research directions in Section 5.

2. Financial indicators selection based on SE-DEA and GRA

Due to the existence of many indicators in financial statement, selecting the indicators most relevant to corporate financial situation is necessary for a DEA model. GRA is a mathematical method that analyzes correlations between series and thereby determines the difference in contribution between a reference series and each comparison series [29]. The GRA method can rank different indicators by determining their grey relational degrees (GRDs), which is regarded as a measure of the similarities and relevancies of discrete data. The aim of using GRA in this study is to calculate the GRDs between financial situation and financial indicators and to select the key influencing indicators. To get the grey relational coefficient (GRC) and the GRD, the GRA method can be summarized as follows.

A financial data matrix of n companies and m indicators is formulated as$F = (x_{ij})_{m\times n}$.

$$F = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix},$$

$$Y = [y_1 \quad y_2 \quad \cdots \quad y_n],$$

where x_{ij} is the value of ith indicator of jth company $(i = 1,2,\ldots,m; j = 1,2,\ldots,n), y_j$ represents the jth company's financial situation. In this paper, we use 1 to represent financial success and 0 to represent financial failure.

In the GRA, when the range of the sequence is large or the standard value is enormous, the function of some indicators will be neglected or underestimated. Therefore, the GRA might produce incorrect results. Due to this, one procedure has to preprocess the data that are related to a group of sequences, which is called grey relational generation [30]. For this purpose, in order to reduce the effect of difference values between maximum and minimum in original sequences and to get the comparable reference and comparison sequences, the original sequence can be normalized as follows.

$$x_0(j) = \frac{y_j}{\frac{1}{n}\sum_{j=1}^{n} y_j}, \tag{1}$$

$$x_i(j) = \frac{x_{ij}}{\frac{1}{n}\sum_{j=1}^{n} x_{ij}}. \tag{2}$$

Consider one data series

$$X_0 = \{\, x_0(1) \quad x_0(2) \quad \ldots \quad x_0(n)\,\}. \tag{3}$$

This data series is set as the reference sequence. Then consider m $(i = 1,2,\ldots,m)$ data series

$$X_i = \{\, x_i(1) \quad x_i(2) \quad \ldots \quad x_i(n)\,\}. \tag{4}$$

These are set as the comparison sequences.

Following data pre-processing, the GRC is calculated as follows

$$\xi_{0i}(j) = \frac{\Delta_{\min} + \rho\Delta_{\max}}{\Delta_{0i}(j) + \rho\Delta_{\max}}, \tag{5}$$

where

$$\Delta_{0i}(j) = |x_i(j) - x_0(j)| \tag{6}$$

is the absolute value of the difference between the two sequences.

$$\Delta_{\max} = \max_i \max_j \{\Delta_{0i}(j)\}, \tag{7}$$

$$\Delta_{\min} = \min_i \min_j \{\Delta_{0i}(j)\}. \tag{8}$$

$\Delta_{\max}$ and $\Delta_{\min}$ are the maximal and minimal proximity, respectively. Meanwhile, ρ is a distinguishing or an identification coefficient ($\rho \in [0,1]$). In many studies, $\rho = 0.5$ is generally adopted. After the GRC has been obtained, Eq. (9) derives the r_{0i} by taking the average of the GRCs that means applying the same weight to both indicators under evaluation, which is also called Non-weighted or equally weighted GRA [31].

$$r_{0i} = r(X_0, X_i) = \frac{1}{n}\sum_{j=1}^{n} \xi_{0i}(j). \tag{9}$$

For financial failure prediction, however, non-weighted GRA will cause significant downgrades to GRDs of some indicators because each indicator may have a different degree of relevance to the financial situation. Moreover, improper weights assigned to irrelative indicators may cause a biased determination and thereby affect the estimated performance. In view of the above, decisive indicators should be given more influential and significant weights in the process of determining the similarity. Then the weighted GRD between the being compared X_i and the reference sequence X_0 is

$$r_{0i} = r(X_0, X_i) = \sum_{j=1}^{n} \omega(j) \cdot \xi_{0i}(j). \tag{10}$$

To calculate r_{0i}, the value of grey relational weight $(j = 1, 2, \ldots, n)$ need to be determined. Various methods have been used to determine the weight $\omega(j)(j = 1, 2, \ldots, n)$, such as experience value [32], analytic hierarchy process [33], etc. A drawback of these methods is the results can be too subjective due to the many artificial factors involved. Moreover, distance-based weight, linear weight, and nonlinear weight [31] are also used to define the weight $\omega(j)$. According to the principle of weight unified, however, these weighted GRA methods require $\sum_{j=1}^{n} \omega(j) = 1$, so the GRDs calculated based on these approaches may not be always optimal. What is more, once the weight $\omega(j)(j = 1, 2, \ldots, n)$ is determined, it will be applied to calculate the GRDs of each indicator, which may cause beneficial effects on some indicators and adverse effects on others so that the GRDs are lack of impartiality and objectivity.

According to the above reasons, a certain method based on the SE-DEA to determine the optimal weights of each indicator is introduced, by which the optimal GRDs can be obtained. The SE-DEA that is proposed by Andersen and Peterson [26] is a kind of improved DEA model and the SE-DEA scores can be bigger than or equal to 1. So the SE-DEA model can adequately compare the DMUs and the results also have better resolution capabilities [34]. Suppose that we have n DMUs. Each DMU$_j$ $(j = 1, 2, \ldots, n)$ produces s different outputs $y_{rj}(r = 1, 2, \ldots, s)$, using m different inputs $x_{ij}(i = 1, 2, \ldots, m)$. Based on the CCR model, the super-efficiency model for efficient DMU$_j$ can be expressed as

$$\begin{aligned} \max \quad & \sum_{r=1}^{s} u_r y_{rj} \\ s.t. \quad & \sum_{i=1}^{m} \omega_i x_{ij} = 1 \\ & \sum_{i=1}^{m} \omega_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0 \\ & j = 1, 2, \ldots, n \\ & \omega_i, \mu_r \geq 0, \ \forall i, r. \end{aligned} \tag{11}$$

To calculate the GRD r_{0i} that can indicate the degree of association between the ith indicator and the financial situation, the SE-DEA model is used to improve the GRA. According to the SE-DEA model, we can assume an input vector that the input values are all 1, and then each indicator can be viewed as a DMU. Its corresponding output value is the GRC of each indicator. The assumed vectors that include m inputs and the $m \times n$ outputs matrix are as follows

$$\underset{\textbf{Inputs}}{\begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}} \quad \underset{\textbf{Outputs}}{\begin{bmatrix} \xi_{01}(1) & \xi_{01}(2) & \cdots & \xi_{01}(n) \\ \xi_{02}(1) & \xi_{02}(2) & \cdots & \xi_{02}(n) \\ \vdots & \vdots & \ddots & \vdots \\ \xi_{0m}(1) & \xi_{0m}(2) & \cdots & \xi_{0m}(n) \end{bmatrix}},$$

where $\xi_{0i}(j)$ means the GRC of the ith indicator of the jth company. Then, the following hybrid model that is based on the SE-DEA improved grey relational analysis can be presented as

$$\begin{aligned} \max \quad & r_{0i} = \sum_{j=1}^{n} \omega(j) \cdot \xi_{0i}(j) \\ s.t. \quad & \omega_0 \times 1 = 1 \\ & \omega_0 \times 1 - \sum_{j=1}^{n} \omega(j) \cdot \xi_{0i}(j) \geq 0 \\ & i = 1, 2, \ldots, m \\ & \omega(j), \omega_0 \geq 0, \ \forall j, \end{aligned} \tag{12}$$

where ω_0 is the inputs weight and $\omega(j)(j = 1, 2, \ldots, n)$ is the output weight, i.e., the weight of each GRC. Formula (12) can be simplified to the following model

$$\begin{aligned} \max \quad & r_{0i} = \sum_{j=1}^{n} \omega(j) \cdot \xi_{0i}(j) \\ s.t. \quad & \sum_{j=1}^{n} \omega(j) \cdot \xi_{0i}(j) \leq 1 \\ & i = 1, 2, \ldots, m \\ & \omega(j) \geq 0, \ \forall j. \end{aligned} \tag{13}$$

By calculating formula (13) m times for m indicators, the optimal solution are obtained as follows.

$$\omega^* = [\,\omega(1)^* \quad \omega(2)^* \quad \cdots \quad \omega(n)^*\,] = \begin{bmatrix} \omega^*_{11} & \omega^*_{12} & \cdots & \omega^*_{1n} \\ \omega^*_{21} & \omega^*_{22} & \cdots & \omega^*_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \omega^*_{m1} & \omega^*_{m2} & \cdots & \omega^*_{mn} \end{bmatrix},$$

$$r^* = [\,r^*_{01} \quad r^*_{02} \quad \cdots \quad r^*_{0m}\,]^T.$$

Generally, according to matrix ω^*, the method integrating the SE-DEA and the GRA can calculate the optimal weights for every indicator of each company, which makes the obtained GRDs more objective and reasonable. Besides, because the SE-DEA can have efficiency scores bigger than 1, the obtained weights value which is calculated by this method does not like the traditional GRA model that requires $\sum_{j=1}^{n}\omega(j) = 1$. Thus, the weights and the GRDs determined by this improved method can more accurately measure the correlation between financial indicators and the financial situation. In this paper, we use the above method to rank and select financial indicators. Furthermore, according to the characteristics of the SE-DEA, the SE-DEA scores namely the GRD bigger than 1 means that the indicator is efficient and also represents that the indicator is closely associated with the financial situation.

3. Two-level DEA model for financial failure prediction

3.1. The indicators system

Although financial indicators, originated in financial statement, can reflect some characteristics of a corporation from various aspects to a certain extent, it is hard to use those indicators directly to evaluate the efficiency of a single corporation.

In this study, a two-level DEA model is used to predict financial failure, and it needs to build a two-level indicator system that includes level indicators and secondary indicators. According to similarity and correlation, financial indicators can be divided into different categories, such as Stability, Profitability, Growth, Activity, Cash flow, etc., and each category contains multiple relevant indicators. If the indicators selected from each category are the most relevant to corporate financial situation, it may use fewer financial indicators for financial failure prediction. There exist a lot of studies on how to choose relevant indicators from different categories for financial failure prediction, e.g., Xu and Wang [35] choose 20 indicators from 5 categories; Kim et al. [36] choose 20 indicators from 6 categories, and Chen et al. [37] choose 37 indicators from 4 categories. Chen et al. [38] and Kim et al. [36] divide indicators into four categories including solvency, operation ability, profitability, and growth ability according to the particularity of China's securities market and the accounting system. These four categories contain a lot of financial indicators, such as liquidity, quick ratio, debt to asset ratio, interest coverage, operating cycle, inventory turnover, etc, which may proxy for the financial strength or weakness and potential insolvency of a corporate. In this study, we construct a two-level indicator system that contains 4 level indicators of solvency, operation ability, profitability, and growth ability as well as 25 secondary indicators such as current ratio, quick ratio, etc as listed in Table 1, which are commonly used in many existing literatures and are considered to be efficient for Chinese listing corporation financial failure prediction [8].

3.2. The two-level DEA model

As we know if the number of input and output indicators is relatively large, the result of the DEA models cannot be very trustable. The simplest method to deal with this shortcoming is to eliminate some indicators and then perform the evaluation process with a smaller number of indicators, which is adopted in many literatures on financial failure prediction based on one-level DEA models. For example, Premachandra et al. [11] use 9 financial indicators, Cielen et al. [10] use 8 indicators,

Table 1
Candidate indicators with hierarchical structure.

Level indicators	The secondary indicators
Solvency	Current liabilities rate (CLR); Current ratio (CR); Asset–liability ratio (ALR); Quick ratio (QR); Cash flow of the debt ratio (CFDR); Total debt to Intangible Assets ratio (TDIAR)
Operation ability	Operating Cash flow ratio (OCFR); Total asset turnover (TAT); Accounts receivable turnover days (ARTD); Total business costs/Total business revenue (TBCR); Operating cycle (OC); Fixed asset turnover (FAT); Inventory turnover rate (ITR); Accounts payable turnover rate (APTR); Account receivable turnover ratio(ARTR); Asset impairment loss/Total business revenue (AILTB)
Profitability	Return on total assets ROA (RTA); Net interest rate of the total assets ROA (NITA); Profit margin on sales (PMS); Ratio of sales to cost (RSC); Total liabilities to EBITDA ratio (TLER); EBIT/Total business revenue (ETB); Net business activities generated cash flow/Business revenue (NALR)
Growth ability	Interest increase ratio (IIR); Growth rate of sales (GRS)

and Du et al. [39] even only use 6 indicators. However, removing highly correlated indicators may not be rational because it is well accepted that the output and input indicators that are highly correlated are needed for comprehensive evaluation of corporate financial situation.

The two-level DEA model proposed by Meng et al. [16] is introduced to use in case that similar inputs or outputs can be grouped into categories, which is suitable for financial failure prediction apparently. According to the indicator system constructed above, a two-level DEA model in which both the inputs and the outputs are grouped into four categories will be built in this section, different from the model proposed by Meng et al. [16] where only outputs are grouped. Suppose that there are n DMUs with m input indicators and s output indicators, the two-level DEA model can be formulated as follows

$$\begin{aligned} \max \quad & \delta = \theta + \varepsilon(S^- + S^+) \\ s.t. \quad & (AX)\lambda + S^- = AX_0 \\ & (BY)\lambda - S^+ = \theta(BY_0) \\ & \sum_{j=1}^{n} \lambda_j = 1 \\ & \lambda_j, S^-, S^+ \geq 0 \\ & j = 1, 2, \ldots, n, \end{aligned} \tag{14}$$

where ε is a non-Archimedean quantity (i.e., a very small positive number); generally, let $\varepsilon = 10^{-6}$. S^- and S^+ are the slack vector variables representing inputs and outputs, respectively. λ_j is the coefficient associated with the selection of an efficient frontier point for the evaluation of DMU_0, and it can either be fixed or allow some variations; δ is the optimal efficiency value of DMU_0.

For formula (14), we impose the following rules:

(a) If δ=1, the DMU_0 is overall efficient;
(b) If δ <1, the DMU_0 is inefficient.

Matrix A is the level input indicators matrix and matrix B is the level output indicators matrix. According to the indicator system introduced above, 25 typical indicators are selected and grouped into four level indicators respectively. So the level indicators matrices A and B are as follows.

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

The level indicators matrices, i.e., A and B, are 4×4 block diagonal matrices, where each 1 represents a level indicator. Each 1 from the first line to the fourth line stands for level indicators of solvency, operation ability, profitability, and growth ability, respectively. Each level indicator of A and B contains several secondary indicators, and the secondary level matrices are as follows.

$$A' = \begin{bmatrix} \omega_{11} & \omega_{12} & \cdots\cdots & \omega_{1h} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \omega_{2,h+1} & \cdots\cdots & \omega_{2k} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \omega_{3,k+1} & \cdots\cdots & \omega_{l} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \omega_{4,l+1} & \cdots\cdots & \omega_{4n} \end{bmatrix},$$

$$B' = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots\cdots & \mu_{1o} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \mu_{2,o+1} & \cdots\cdots & \mu_{2p} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mu_{3,p+1} & \cdots\cdots & \mu_{3q} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mu_{4,q+1} & \cdots\cdots & \mu_{4m} \end{bmatrix}.$$

A' and B' are $4 \times n$ and $4 \times m$ matrices, respectively, where n is the number of input indicators and m is the number of output indicators. $\omega_{i\alpha}(i = 1, \ldots, 4, \alpha = 1, 2, \ldots, n)$ is the weight of the αth secondary indicator that belongs to the ith input level indicator. While $\mu_{j\beta}(j = 1, \ldots, 4, \beta = 1, 2, \ldots, m)$ is the weight of the βth secondary indicator that belongs to the jth output level indicator. Besides, we have that

$$\begin{aligned} &\sum_{\alpha=1}^{h} \omega_{1\alpha} = 1, \quad \sum_{\alpha=h+1}^{k} \omega_{2\alpha} = 1, \quad \sum_{\alpha=k+1}^{l} \omega_{3\alpha} = 1, \quad \sum_{\alpha=l+1}^{n} \omega_{4\alpha} = 1, \\ &\sum_{\beta=1}^{o} \mu_{1\beta} = 1, \quad \sum_{\beta=o+1}^{p} \mu_{2\beta} = 1, \quad \sum_{\beta=p+1}^{q} \mu_{3\beta} = 1, \quad \sum_{\beta=q+1}^{m} \mu_{4\beta} = 1. \end{aligned} \tag{15}$$

The weight determination needs to measure the importance of each secondary indicator relative to the associated level indicator. For financial indicators, however, it is difficult to compare and measure such importance because the indicators are categorized into the same level indicator only on the basis of similar financial characteristics, which does not mean any contributions to the level indicator. We also have not found any relative literatures on this. Certainly we can measure the importance and then determine the weight by the expert scoring method. The results, however, may have a certain degree of subjectivity. So the secondary indicators that belong to the same level indicator are regarded as equally important in this study and this method is also adopted by Meng et al. [16]. Then we can get the weights as follows.

$$\begin{aligned} &\omega_{1\alpha} = \frac{1}{h}; \quad \omega_{2\alpha} = \frac{1}{k-h}; \quad \omega_{3\alpha} = \frac{1}{l-k}; \quad \omega_{4\alpha} = \frac{1}{n-l}, \\ &\mu_{1\beta} = \frac{1}{o}; \quad \mu_{2\beta} = \frac{1}{p-o}; \quad \mu_{3\beta} = \frac{1}{q-p}; \quad \mu_{4\beta} = \frac{1}{m-q}. \end{aligned} \tag{16}$$

According to the formula (16), those indicators on the same level are on equal status through sharing the same weights.

4. Empirical analysis

4.1. Data and indicators

In order to validate the efficiency of the aforementioned two methods, namely the approach combined the SE-DEA and the GRA for indicators selection and the two-level DEA model for financial failure prediction of companies in China, this study uses companies listed in the Shenzhen Stock Exchange Market (SSEM) for the empirical research. Due to the limitation of the data availability, we can only obtain 15 financial failure companies that are marked ST, *ST, and S*ST with complete data. In this study, we randomly choose 60 financial normal companies that are also called non-ST by the column of 1:4, so there are 75 companies in total.

Special treatment, including ST, *ST, and S*ST, is the particularity of Chinese capital environment [40]. According to Chen et al. [41], the ST companies are those that are special treated as negative net profits in consecutive years; the *ST companies are those that suffer from losses for three consecutive years; and the S*ST companies are those that suffer from losses for four consecutive years, while the non-ST companies are those that have non-crisis. Relative to the ST, companies that are *ST are worse in financial situation, and the company that is marked the S*ST has the most serious financial problems. In order to get more objective and persuasive results, we use the data of 3 years from 2010 to 2012 of the 75 companies for empirical research, which means that the dataset of this study contains 225 samples, covering 12 economic sectors such as industrial, real estate, transportation and warehousing, etc. in order to avoid selection bias.

Using the hybrid approach of the SE-DEA and the GRA introduced in Section 2, we calculate the GRDs between 25 financial indicators listed in Table 1 with financial situation. There are 15 indicators whose GRD are greater than 1. According to the character of the SE-DEA model, these 15 indicators have the closest relevance to financial situation. So we choose these 15 indicators for financial failure prediction by the two-level DEA model in this section.

In the two-level DEA applications, inputs and outputs used for the evaluation of DMUs are needed [16], so those 15 indicators are divided into inputs and outputs as shown in Tables 2 and 3, respectively. In order to compare the result of the indicators selection, the result of 15 indicators whose GRD are the top 15 highest calculated by the traditional GRA is also shown in Tables 2 and 3. From Tables 2 and 3, we can observe that the results calculated by the traditional GRA and the hybrid approach combined the SE-DEA and the GRA are different. To see it clearly, the 15 indicators respectively selected by the two approaches are not completely the same, and the ranks of the 15 indicators are also different.

Tables 2 and 3 also show that the result of 15 indicators whose GRD are the top 15 highest calculated by the traditional GRA can only be divided into three categories. In this condition, according to the indicators system constructed above, the matrix A and $B$are as follows.

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

Then, the secondary level matrices are as follows.

$$A' = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1/4 & 1/4 & 1/4 & 1/4 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \quad B' = \begin{bmatrix} 1/5 & 1/5 & 1/5 & 1/5 & 1/5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1/3 & 1/3 & 1/3 \end{bmatrix}.$$

4.2. Comparisons of different DEA models

Table 4 summarizes the DEA efficiency scores and DEA-based financial failure prediction. The numbers in the descriptive statistics of Table 4 indicate the average, median, maximum, minimum, and variance of efficiency scores measured by the

Table 2
The input indicators.

Level indicator	SE-DEA + GRA			GRA		
	Secondary indicator	GRD	Rank	Secondary indicator	GRD	Rank
Solvency	CLT	1.0081	2	TDIAR	0.9753	13
	ALT	1.0054	7			
Operation ability	TBCR	1.0021	9	TBCR	0.9962	3
	ARTD	1.0013	13	RSC	0.9946	4
				OC	0.9858	8
				AILTB	0.9693	15
Profitability	NALR	1.0020	11	ETB	0.9848	9
	RSC	1.0014	12			
Growth ability	GRS	1.0021	10			

Table 3
The output indicators.

Level indicator	SE-DEA + GRA			GRA		
	Secondary indicator	GRD	Rank	Secondary indicator	GRD	Rank
Solvency	CR	1.0073	4	CLR	0.9969	1
	OCFR	1.0062	6	ALR	0.9963	2
	QR	1.0010	14	CR	0.9937	5
	CFDR	1.0010	15	QR	0.9875	7
				TLER	0.9815	10
Operation ability	TAT	1.0046	8	TAT	0.9703	14
Profitability	RTA	1.0081	3	RTA	0.9811	11
	NITA	1.0071	5	PMS	0.9886	6
				NITA	0.9807	12
Growth ability	IIR	1.0091	1			

three different DEA models. Through the statistical analysis of Table 4, the average scores of the ST companies are 0.6145 (Two-level DEA), 0.7356 (CCR), and 0.7527 (BCC). The variance scores of the ST companies calculated by the three different DEA models are 0.0832 (CCR), 0.0731 (BCC), and 0.0658 (Two-level DEA). Those results show that compared with the CCR and BCC models, the two-level DEA model has better ability to identify and classify the ST companies because the lowest average and variance values of efficiency scores (In the DEA model, the lower the efficiency score, the worse the financial situation. Besides, in statistical analysis, the lower variance shows the smaller fluctuations in the vicinity of the average data). Meanwhile, the average and variance scores of the non-ST companies calculated by the two-level DEA model are 0.9955 and 0.0005, respectively, which are the maximum average scores and the lowest variance scores of the three different DEA models. These also demonstrate that the two-level DEA model has the excellent ability to identify and classify.

Table 4 also indicates two important findings. First, the overall correct evaluations of these three DEA models range from 83.56% to 91.56%. The correct classification rate of the two-level DEA model is 91.56% so the two-level DEA performs extremely well in the three types of the DEA models. Second, the two-level DEA yields 84.44% in the correct classification rate of financial failure corporate (P(FC/FC)). This implies that the error of Type II, P(FC/NFC), is 15.56% which is the lowest of those DEA assessment results. This also means that the two-level DEA has more effective and better assessment ability. In addition, as found in Table 4, this is the major difference in probability assessment (P(FC/FC), P(NFC/NFC), P(NFC/FC), and P(FC/NFC)) as well as correct and incorrect classification rates. The results calculated by the two-level DEA model are obviously superior to those calculated by the other DEA models.

Table 5 summarizes the results of the three DEA models (two-level DEA, CCR, BCC) from 2010–2012. The error of Type II, P(FC/NFC), which are calculated by the two-level DEA from 2010–2012 are 20.00%, 13.33%, 13.33% and the error of Type I, P(NFC/FC), which are calculated by the two-level DEA from 2010–2012 are 8.33%, 6.67%, 5.00%. These results are obviously lower than those (for example the error of Type I, P(NFC/FC), which are calculated by the CCR model, ranges from 11.67%-13.33%) of the other DEA models as well as correct and incorrect classification rates. Table 5 also indicates that the two-level DEA attains the high correct classification rate (89.33–93.33%) by both reducing the Type I error and slightly reducing the Type II error.

This study uses 45 samples from 2010 to 2012 which are identified as ST, *ST, and S*ST, respectively. Generally, financial crisis prediction models have more emphasis on the ability to classify the bankrupt companies since the Type II error will generate huge financial risks. Therefore, this paper further analyzes the assessment results of the bankrupt companies including ST, *ST, S*ST, as shown in Table 6.

Table 4
Results of three DEA models.

Model	CCR		BCC		Two-level DEA	
Company	ST	Non-ST	ST	Non-ST	ST	Non-ST
Descriptive statistics						
Average	0.7356	0.9919	0.7527	0.9926	0.6145	0.9955
Median	0.8396	1.0000	0.8325	1.0000	0.6509	1.0000
Maximum	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Minimum	0.1063	0.8179	0.1234	0.8341	0.1349	0.8210
Variance	0.0832	0.0008	0.0731	0.0006	0.0658	0.0005
P(FC/FC)	68.89%		64.44%		84.44%	
P(NFC/NFC)	87.22%		87.78%		93.33%	
P(NFC/FC)	12.78%		12.22%		6.67%	
P(FC/NFC)	31.11%		35.56%		15.56%	
Correct classification	83.56%		83.11%		91.56%	
Incorrect classification	16.44%		16.89%		8.44%	

(a) P(FC/FC): percentage of financial failure companies predicted as financial failure. P(NFC/NFC): percentage of non-financial failure companies predicted as non-financial failure.
(b) Type I error corresponding to P(NFC/FC) is the percentage of non-financial failure companies are misclassified as financial failure companies. Type II error corresponding to P(FC/NFC) is the percentage of financial failure companies are misclassified as non-financial failure companies.
(c) The correct classification is the percentage of companies predicted correctly in all companies. The incorrect classification is (1- the correct classification).

Table 5
The results of three DEA models in 2010–2012.

Model	2010			2011			2012		
	Two-level DEA (%)	CCR (%)	BCC (%)	Two-level DEA (%)	CCR (%)	BCC (%)	Two-level DEA (%)	CCR (%)	BCC (%)
P(FC/FC)	80.00	66.67	66.67	86.67	66.67	66.67	86.67	73.33	60.00
P(NFC/NFC)	91.67	86.67	88.33	93.33	86.67	88.33	95.00	88.33	86.67
P(NFC/FC)	8.33	13.33	11.67	6.67	13.33	11.67	5.00	11.67	13.33
P(FC/NFC)	20.00	33.33	33.33	13.33	33.33	33.33	13.33	26.67	40.00
Correct classification	89.33	82.67	84.00	92.00	82.67	84.00	93.33	85.33	81.33
Incorrect classification	10.67	17.33	16.00	8.00	17.33	16.00	6.67	14.67	18.67

As shown in Table 6, this paper uses the average, median, maximum, minimum, and variance of efficiency scores measured by the three different DEA models for descriptive statistical analysis. Table 6 confirms that the average efficiency scores of the two-level DEA are lower than those of the other DEA models in terms of all bankrupt companies including ST, *ST, and S*ST except the ST companies average efficiency score of the CCR model, which suggests that the results of the two-level DEA can be a more accurate assessment of the company's financial situation. Besides, in the two-level DEA model, the difference between the average of the ST companies and the *ST companies is 0.168 while the difference between the average of the *ST companies and the S*ST companies is 0.475, both of which are higher than the difference between the average of the corresponding results of the CCR model and the BCC model. This also shows that the two-level DEA has a better ability on assessment. Meanwhile, the variance scores of the two-level DEA are 0.0151, 0.0585, and 0.00000009 (represented as 0.0000* in Table 6), which are the lowest variance scores of the ST, *ST, and S*ST three types of companies. Thus, the two-level DEA model has the excellent ability to assess the different companies in financial situation.

In order to find the effectiveness of the hybrid approach of the SE-DEA and the GRA for feature selection, this paper uses another Top 15 indicators that is selected by the traditional GRA as shown in Tables 2 and 3 to evaluate the three kinds of DEA efficiency scores as shown in Table 7.

Table 6
Statistical analysis of ST, *ST, and S*ST.

Model	CCR			BCC			Two-level DEA		
Company	ST	*ST	S*ST	ST	*ST	S*ST	ST	*ST	S*ST
Descriptive statistics									
Average	0.7624	0.7790	0.1613	0.7999	0.7697	0.4546	0.7895	0.6219	0.1469
Median	0.8133	0.8442	0.1467	0.8163	0.8335	0.2213	0.7478	0.5439	0.1471
Maximum	1.0000	1.0000	0.2307	1.0000	1.0000	1.0000	1.0000	1.0000	0.1471
Minimum	0.4553	0.1264	0.1063	0.6131	0.1234	0.1423	0.6592	0.1349	0.1466
Variance	0.0397	0.0684	0.0040	0.0239	0.0673	0.2247	0.0151	0.0585	0.0000*
Correct classification	83.33%	63.89%	100.00%	83.33%	61.11%	66.67%	83.33%	83.33%	100.00%
Incorrect classification	16.67%	36.11%	0.00%	16.67 %	38.89%	33.33%	16.67%	16.67%	0.00%

Table 7
Results of three DEA models based on traditional GRA for indicators selection.

Model	Two-level DEA				CCR				BCC			
Company	ST	*ST	S*ST	Non-ST	ST	*ST	S*ST	Non-ST	ST	*ST	S*ST	Non-ST
Descriptive statistics												
Average	0.9480	0.8829	0.2418	0.9925	0.9189	0.8708	1.0000	0.9905	0.9166	0.8907	0.9928	0.9926
Median	0.9919	0.8919	0.2328	1.0000	0.9271	0.9095	1.0000	1.0000	0.9288	0.9207	1.0000	1.0000
Maximum	1.0000	1.0000	0.4670	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Minimum	0.8133	0.6401	0.0258	0.8333	0.8232	0.2670	1.0000	0.8355	0.8093	0.2670	0.9784	0.8393
Variance	0.0062	0.0111	0.0487	0.0007	0.0079	0.0243	0.0000	0.0008	0.0085	0.0251	0.0002	0.0006
P(FC/FC)		73.33%				71.11%				71.11%		
P(NFC/NFC)		85.00%				84.44%				85.00%		
P(NFC/FC)		15.00%				15.56%				15.00%		
P(FC/NFC)		26.67%				28.89%				28.89%		
Correct classification		82.67%				81.78%				82.22%		
Incorrect classification		17.33%				18.22%				17.78%		

As listed in the bottom of Table 7, the overall correct classification measured by the two-level DEA is 82.67%. In contrast, the overall correct classifications measured by the CCR model and the BCC model are 81.78% and 82.22%, respectively. Moreover, those correct classification rate of default companies (P(FC/FC)) and non-default companies (P(NFC/NFC)) measured by the two-level DEA are 73.33% and 85.00%, respectively, which are the highest of those DEA assessment results. Thus, the results shown in Table 7 illustrate once again that the two-level DEA has more effective and better assessment ability than the CCR and BCC models. However, compared with Table 4, the two-level DEA results shown in Table 7 are far less than the results in Table 4, for example, the overall correct classification shown on Table 4 is 91.56% that is higher than 82.67% of Table 7. Therefore, the approach combined the SE-DEA and the GRA that is proposed in this paper is very effective.

5. Conclusions and future research

In this paper, we develop and implement a framework of a corporate financial failure predicting model based solely on publicly available data. To this end, the two-level DEA model is used to introduce a financial failure predicting model, based on publicly available financial data listed in the SSEM. This model can be easily employed to evaluate corporates in order to obtain the assessed value of its financial situation. To use the two-level DEA model, we need to use the approach combined the SE-DEA and the GRA to select the high relevant financial indicators from a large set of candidate indicators as inputs and outputs. The empirical application of this approach based on the data from the SSEM leads to promising results. The obtained results demonstrate that the predictability of the two-level DEA model is very competitive compared with the traditional one-level DEA models fitted on the historical financial failure companies' data no matter using the 15 indicators or 25 indicators for implementation. The obtained results also demonstrate that, the approach combined the SE-DEA and the GRA for indicators selection is very effective, and the two-level DEA model provides better classification results with the indicators selected. In future, it will be also interesting to apply the framework to analyze facility and supply chain network efficiency [42,43].

Acknowledgments

This research was supported by the National Natural Science Foundation of China Grant (No. 71201024) and the Fundamental Research Funds for the Central Universities of China Grant (No. SKCX20120023).

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