SMEs Credit Rating Method with Heterogeneous Information: a Chinese Case

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Abstract

Enterprise credit rating is an important issue in finance field. Small and Medium Enterprises are playing more and more important role in world economy development. Especially, China SMEs has gained rapid development in recent years. However, financing difficulty is a predominant and common problem for the SMEs in China. It needs joint effort to solve the SMEs financing embarrassment. One of the solution is to establish a reasonable SMEs credit rating method which can produce a convincing credit rating result. The paper presents a SMEs credit rating method with heterogeneous information based on currently used credit criterion system in China.

Keywords: Fuzzy set, Numerical value, Heterogeneous information, SMEs credit rating, Decision making

1. Introduction

Financing difficulty of SMEs is a common problem all over the world. The same situation also exists in China. SMEs are playing more and more important role in Chinese economy development. Of more than 10,000 registered firms, the medium-small-size firms are 99.3%. They contribute 55.6% of GDP. However, the SMEs just get 16% loaning from main financial institutions, only 30% loaning need is met for some high quality SMEs[1]. The financing difficulty has become the main obstacle of SMEs rapid development.

The reason of SMEs financing embarrassment is various. One of the reason is that the lack of enough credible SMEs credit rating record. As it is described in literature [14], "Asymmetric information between borrowers and lenders, which is a defining characteristic of all credit markets, is particularly acute in the informationally opaque market for small business credit. Small businesses pose a particular challenge for lenders because of their lack of audited financial statements, commingling of the owner's personal finances and those of the business and because of their diversity". On one hand, bank may refuse to lend to SMEs because of the lack or low credit in order to avoid high risk. On the other hand, financial institutions have to follow the same procedure to evaluate the credit of SMEs for the "small amount of loaning" requirement of SMEs as that of used in large-scale enterprise credit rating. The same processing procedure will lead to high management cost for every unit loaning sum for bank.

An easy-to-use and reliable SMEs credit rating method may be helpful to solve the SMEs finance difficulty. Based on currently used SMEs credit rating system in China and some financial experts' opinion, we propose a SMEs credit rating method with heterogeneous information in this paper.

The paper is organized as follows. Some related research literature on SMEs credit rating problem are reviewed in section 2. Then the problem formulation of SMEs credit rating is described in section 3, the SMEs credit rating is recognized as a hierarchical multi-criteria decision problem with heterogeneous information. It follows a SMEs credit rating method with heterogeneous information in section 4. Conclusions are given in section 5.

2. Literature review

With the rapid development of SMEs and common financing difficulty faced by SMEs, research on SMEs financing and credit rating method has drawn a lot of attention of both academy and industry all over the world.

In 2000, A. R. Levenson et al. measures the extent to which small businesses in the United States

[1]The data is excerpted from the paper "SMEs are facing financing embarrassment and it needs Joint Effort" on Economy Daily, written by Z. F. Chen

in the late 1980s were able to access the external credit finance they desired in literature [2]. In 2005, A. N. Berger et al discusses credit scoring technology which is used in U. S. commercial bank, evaluates the research findings on the effects of credit scoring technology on small business credit availability, and links these findings to a number of research and public policy issues in literature [1]. In 2005, E. I. Altman et al. develop a distress prediction model specifically for the SME sector and to analyze its effectiveness compared to a generic corporate model in literature [6].

In addition, there are some research literatures on Chinese SME financing and credit scoring research as follows. In 2003, Y. L. Dong et al. perform an application analysis of credit scoring in Chinese SMEs loaning in literature [21] and they come to the conclusion that credit rating may be useful for SMEs financing difficulty. In 2004, W. Y. Wang et al. discuss a double layer of SMEs credit rating and its evaluation model in literature [19] and they proposed to establish a SMEs credit rating model which combines enterprise financial condition and entrepreneur personnel information. In 2005, T. L. Zhong propose a Neural Network method of SMEs credit rating based on Chinese SMEs in literature [18]. In 2005, L. F. Fan et al. propose to establish commercial bank credit rating system adaptive to SMEs in literature [12] and they propose that a credit rating method which is suitable for SMEs should change current criteria system and combine the credit rating with the industry background. In 2005, Z. Y. Zhao et al. propose a credit scoring model which is based on the financial status and quantitative information of the entrepreneur of the SMEs in China in literature [25] and they think the proposed model is more exact than current credit rating model. In 2006, J. M. Wu et al. propose some solution to make SMEs financing easier in literature [11].

In addition, there are a lot of literatures on credit rating system and methods. Some of them are based on statistical and machine learning method including Logistic Regression, Neural Network [3, 5], Decision Tree Classification, Multivariate Discriminant Approach (MDA), Support Vector Machine [4, 20, 24], k-nearest neighbor or hybrid intelligent method [16] etc. And there are other research which is based on expert system, decision making system or hierarchical model. Moreover, because of the existence of fuzziness in the process of credit rating, some literatures try to solve the credit rating problem based on fuzzy sets and its related methods[13, 17, 22, 23].

3. Problem formulation

As described in the former section, there are a lot of research literatures on SMEs credit rating. But they can't solve the SMEs credit rating in China for the following reasons. First, these credit rating methods based on statistical method or machine learning method should be based on enterprise credit database. However, different financial institution doesn't share the SMEs credit data in China. There is no data pool of SMEs credit rating database. So it is difficult to use the existed credit rating method based on statistical or machine learning method. Second, the SMEs credit rating criteria framework should include not only enterprise financial condition and entrepreneur personnel credit records, but also the enterprise development perspective etc. Last but not least, The SMEs credit rating system includes not only financial criteria which is numerical, but also other criteria such as development ability and promising, management measure etc which may be linguistic. It is necessary to establish a SMEs credit rating system and its corresponding method which is suitable for SMEs.

Based on the SMEs credit rating criteria system which is currently used in China and some financial experts' opinion, the SME credit rating criteria framework is concluded as follows. The framework includes five main categories: Financial Conditions, Characteristic and Perspective of the product, Operation Risk and Competitive Strength, Management Measure and Conditions of Industry of evaluated SMEs. Every main category also includes several sub-criteria. In addition, different sub-criteria may have various kind of evaluation value on their respective scale units. Some evaluation value of the sub-criteria are numerical, others are linguistic. The corresponding type of value for each sub-criterion is also given respectively as follows.

1. Financial Conditions
    - Liquidity ratios
        - Quick ratio (Percentage)
        - Current ratio (Percentage)
    - Leverage ratios
        - Times-interest-earned (times)
        - Total debt to assets (percentage)
        - Debt to equity ratio (Percentage)
    - Profitability ratios
        - profit margin (Percentage)
        - ROS, i.e. rate of sales (Percentage)

- ROA, i.e. return on assets (Percentage)
  - return on net assets(Percentage)
  - ROE, return on equity (Percentage)
- Efficiency ratios
  - Inventory turnover (time)
  - Receivable turnover (time)
  - Assets turnover (time)
- Development Ability
  - average sale growth rate during the last three years [2](Percentage)
  - conditions of capital increment during the last three years (Percentage)
  - total profit growth rate (Percentage)

2. Characteristic and Perspective of the products
   - product marketability (Linguistic value)
   - product market share (Percentage)
   - product perspective (Linguistic value)
3. Operation Risk and Competitive Strength
   - running risk (Linguistic value)
   - technologies and R&D ability (Linguistic value)
4. Management Measure
   - administrator's personal credit (Linguistic value)
   - administrator's management experience and knowledge structure (Linguistic value)
   - integrity and perfection of management system (Linguistic value)
   - stockholders structure type (Linguistic value)
5. Conditions of Industry
   - Macro-industry policies (Linguistic value)
   - industry risk in the next year (Linguistic value)
   - economic condition prediction in the next year (Linguistic value)

Here we list possible assessment value of attribute with linguistic value as follows [3].

- product marketability (Linguistic value such as "Very High, High, Medium, Low, Very Low")
- running risk (Linguistic value such as "Very High, High, Medium, Low, Very Low")
- technologies and R&D ability (Linguistic value such as "very weak, medium, strong, very competitive and advanced")
- industry conditions prediction in the next year (Linguistic value such as "rapid decrease, slow decrease, stable, slow increase, rapid increase")
- administrator's personal credit(Linguistic value such as "Very Bad, Bad, Medium, Good, Very Good")
- administrator's management experience and knowledge structure(Linguistic value such as "Very Bad, Bad, Medium, Good, Very Good")
- integrity and perfection of management system (Fuzzy or Linguistic value "Very Bad, Bad, Medium, Good, Very Good")
- stockholders structure type (Linguistic value such as "Very Bad, Bad, Medium, Good, Very Good")
- Macro-industry policies (Linguistic value such as "inconsistent, partly consistent, completely consistent")
- industry risk in the next year (Linguistic value such as "Very High, High, Medium, Low, Very Low")
- economic condition prediction in the next year (Linguistic value such as "rapidly decrease, slowly decrease, stable, slowly increase, rapidly increase")

It is obvious that linguistic or fuzzy evaluation value does exist in SMEs credit rating system. There are also some existed literatures on credit rating methods and models which are based on fuzzy numbers as follows. In 1999, H. J. Rommelfanger propose a fuzzy logic based systems for checking the credit solvency of small business firms in literature [10]. In 1999, L. H. Chen et al. propose a fuzzy credit-rating approach for commercial loans on taiwan cases in literature [13]. In 1999, R. Weber propose application of fuzzy logic for credit worthiness evaluation in literature [17]. In 2001, Y. R. Syau et al. propose fuzzy numbers in the credit rating of enterprise financial condition in literature [23]. In 2006, Y. Jiao et al propose a modelling credit rating by using fuzzy adaptive Neural Network in literature [22]. In these above literatures, both quantitative and fuzzy information are dealt with by fuzzy numbers.

However, as it is described in literature [7], "the linguistic method may lead to loss of information". So 2-tuple fuzzy representation model for computing with words is proposed in literature [7]. Moreover, F. Herrera et al. propose a method to deal with non-homogeneous information in group decision making in literature [9] in 2005. In addition, L. Martinez et al. propose a method dealing with heterogeneous information in engineering evaluation process in literature [15]. The above proposed

[2] If the recorded sale growth rate is less than three year, take the average of the most recent recorded value

[3] The above linguistic term set may apply with the different SMEs and the corresponding industry.

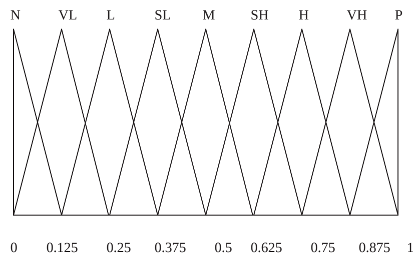

Fig. 1: Semantic of Set of Standard Linguistic Term Sets

method in the literatures [9, 15] can represent and aggregate heterogeneous information with diverse form or different information granularity. Based on the above research result, we will propose a method dealing with heterogeneous information in SMEs credit rating based on linguistic 2-tuples.

4. Credit rating method with heterogeneous information

4.1. Choosing the standard linguistic term set

The credit institution usually uses the following nine grades "C, CC, CCC, B, BB, BBB, A, AA, AAA" from lowest to highest to denote the loaning enterprises credit rating classes. Accordingly, we define a standard linguistic term set T to denote the credit rating classes without crisp partition, which includes nine fuzzy sets corresponding to the nine corresponding grades as follows: $T = \{s_k | k = 0, 1, \cdots, 8\} = \{s_0$: None (abbr. to N), s_1 : Very Low (abbr. to VL), s_2 : Low (abbr. to L), s_3 : Slightly Low (abbr. to SL), s_4 : Medium (abbr. to M), s_5 : Slightly High (abbr. to SH), s_6 : High (abbr. to H), s_7 : Very High (abbr. to VH), s_8 : Perfect (abbr. to P) $\}$. And we can define an order on T as follows: $s_i \leq s_j \Leftrightarrow i \leq j$. We take triangular fuzzy set $s_k = (a_k, b_k, c_k)$ to denote every fuzzy set $s_k, (k = 0, 1, 2, \cdots, 8)$, where a_k denotes the left limit of the definition domain of the triangular membership function, c_k denotes the right limit of the definition domain of the triangular membership function, b_k denotes the value in which the membership value is 1. Its corresponding semantic is described as in figure 1.

4.2. Dealing with numerical value

The related financial criteria values are given in numerical form. These numerical values include percentage, time and times according to their original form. In addition, even for the same form of numerical value or certain equal value, it may account for different contribution to the final evaluation result besides their corresponding important coefficient, i. e., we should use relative value other than an absolutely one in aggregation process. Moreover, the corresponding financial evaluation standard should vary with the industry. Accordingly, it will make sense to evaluate an enterprise from the point of view of the same or similar industry. Here we give the definition 4.1 to transform the absolute financial value to a relative one which is belongs to [0,1].

Definition 4.1 *Let "max" be the industry optimal value, "min" the industry worst value, "ave" the industry average value of certain evaluated criterion* C_{ij} *respectively, nv be the given evaluation value, define a function* f *which transforms the absolute numerical one nv to a relative value* $f(nv) \in [0, 1]$ *as follows:*

$$f : R \to [0, 1] :$$

$$f(x) = \begin{cases} min\{1, 1 - \dfrac{max - x}{max}\}, & x > avg, \\ 0.5, & x = avg, \\ max\{0, \dfrac{x - min}{min}\}, & x < avg, \end{cases} \qquad (1)$$

Then transform all numerical value in [0,1] to fuzzy sets in standard linguistic term set T as in definition 4.2.

Definition 4.2 *Let* $T = \{s_k | k = 0, 1, \cdots, 8\} = \{s_0$ *: None (abbr. to N),* s_1 *: Very Low (abbr. to VL),* s_2 *: Low (abbr. to L),* s_3 *: Slightly Low (abbr. to SL),* s_4 *: Medium (abbr. to M),* s_5 *: Slightly High (abbr. to SH),* s_6 *: High (abbr. to H),* s_7 *: Very High (abbr. to VH),* s_8 *: Perfect (abbr. to P)* $\}$ *be a standard linguistic term set, define transformation function* τ *from numerical value in [0, 1] into fuzzy sets in* T *as follows:*

$$\tau : [0, 1] \to F(T),$$
$$\tau(v) = \{(s_0, \gamma_0), (s_1, \gamma_1), \cdots, (s_8, \gamma_8)\},$$

$s_i \in T, r_i \in [0,1]$

$$\gamma_i = \mu_{s_i}(v) = \begin{cases} 0, & \textit{if } v \notin \textit{Support}(\mu_{s_i}(v)), \\ \dfrac{v-a_i}{b_i-a_i}, & \textit{if } a_i < v < b_i, \\ 1, & \textit{if } v = b_i, \\ \dfrac{c_i-v}{c_i-b_i}, & \textit{if } b_i < v < c_i \end{cases} \tag{2}$$

4.3. Dealing with linguistic value

We take fuzzy sets to denote the assessment value of qualitative criteria considering their linguistic and fuzzy nature. Various evaluated qualitative criteria may have various evaluation scale according to expert consensus, i. e. distinct "information granularity". We take the following function ψ defined in definition 4.3 similar to that of in literature[15] to transform all linguistic evaluation values into fuzzy sets in T in order to prevent the deviation between final aggregation value and value in real case.

Definition 4.3 *[15] Let S be an evaluation linguistic term set, T be the standard linguistic term set and $lv \in S$ be a linguistic term provided by experts. We define the transformation function ψ from S into fuzzy sets in standard fuzzy sets T as follows:*

$$\begin{aligned} &\psi : S \rightarrow T : \\ &\psi(lv) = \{(s_0, \gamma_0), (s_1, \gamma_1), \cdots, (s_8, \gamma_8)\}, \\ &\gamma_i = \max_y min\{\mu_{lv}(y), \mu s_k(y)\}, \end{aligned} \tag{3}$$

where $\mu_{lv}(y), \mu s_k(y)$ are the membership functions of the fuzzy sets associated with the terms lv and s_k, respectively.

Both numerical and qualitative values will be transformed to fuzzy sets in standard fuzzy sets T by using the transformation defined in definition 4.1,4.2,4.3. Enlightened by the idea in literature [8, 9], we shall transforms these collective fuzzy sets into linguistic 2-tuples in standard linguistic term set T as in definition 4.4 defined in literature [15] to facilitate the ranking process of final enterprise credit rating result,.

Then we transform all fuzzy sets in T into the linguistic 2-tuples in T by using the transformation function in definition 4.4 as defined in literature [15].

Definition 4.4 *[15] Transform the fuzzy sets in S_s into the linguistic 2-tuples in S_s:*

$$\begin{aligned} &\mathcal{X} : F(S_s) \rightarrow S_s \times [-0.5, 0.5), \\ &\mathcal{X}(\tau(v)) \\ &= \mathcal{X}(\{(s_j, \gamma_j), j = 0, 1, \cdots, g\}) \\ &= \triangle(\sum_{j=0}^{g} j \cdot \gamma_j / \sum_{j=0}^{g} \gamma_j) \end{aligned} \tag{4}$$

4.4. Aggregation

After transform all the assessment values into linguistic 2-tuples in standard linguistic term set T, we can aggregate all the transformed values by using the weighted average operators defined as in definition 4.5 presented in literature [7] in our SME credit rating method.

Definition 4.5 *[7] Let $x = \{(r_1, \alpha_1), (r_2, \alpha_2), \cdots, (r_n, \alpha_n)\}$ be a set of 2-tuples and $W = (\omega_1, \omega_2, \cdots, \omega_n)$ be their associated vector. Then the weighted aggregation operator on 2-tuple is defined as:*

$$\begin{aligned} &x \circ W \\ &= \triangle(\frac{\sum_{i=1}^{n} \triangle^{-1}(r_i, \alpha_i) \cdot \omega_i}{\sum_{i=1}^{n} \omega_i}) \\ &= \triangle(\frac{\sum_{i=1}^{n} \beta_i \cdot \omega_i}{\sum_{i=1}^{n} \omega_i}) \end{aligned} \tag{5}$$

4.5. Summary of credit rating method

Concretely, the credit rating method is as follows:

1. Transformation;
   - For numerical value nv,
     (a) We transform every numerical evaluation value nv to a relative value $f(nv)$, where $f(nv) \in [0,1]$;
     (b) Transform the relative value $f(nv)$ into fuzzy sets $\tau(f(nv))$ in T;
     (c) Transform fuzzy sets in T to $\mathcal{X}(\tau(f(nv)))$linguistic 2-tuples in T.
   - For linguistic value lv,
     (a) Transform the linguistic value lv into fuzzy sets in T as $\psi(lv)$;
     (b) Transform fuzzy sets in T to linguistic 2-tuples in T as $\mathcal{X}\psi(lv)$.
2. Aggregation as in definition 4.5 with these transformed value which are fuzzy sets in T and weighting vector $(\omega_1, \omega_2, \cdots, \omega_m)$, where m is the number of evaluated criteria.

5. Conclusions

In this paper, a SMEs credit rating method with heterogeneous information is proposed. It is one of possible solution of SMEs financing difficulty. The method is feasible and easy-to-use. However, it is only a framework of SMEs credit rating. It needs more industry background data set to consummate the SMEs distributing in various industry credit rating method.

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