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*Original Paper*

# Credit Decision Problems of MSMEs (Medium, Small and Micro-sized Enterprises)

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***Abstract***

*Micro, small and medium enterprises (MSMEs) have become an important force in driving the country's market economy in the 21st century. However, because of the following drawbacks: i.e. single enterprise capital chain, unstable economy, high risk, etc., banks will take many risks if they lend to MSMEs. Therefore, it is necessary to build a sound bank credit decision system to promote the development of MSMEs.*

*The analytic hierarchy process (AHP) is employed to classify the importance level such as credit rating and enterprise strength are used as first-grade indexes, and six indicators in terms of total sales and total profits are used as the second-grade indexes. Then, the eigenvalue method is used to obtain the importance weights of each level of indicators, and the weights of each influencing factor at each level are then calculated to achieve a quantitative analysis of credit risk and rating of each enterprise's credit risk. This paper combines the existing loan pricing and loan interest rates to give preferential interest rates and higher loan amounts to enterprises with excellent credit risk ratings, and to give certain risky interest rates and lower loan amounts to enterprises with medium credit risk ratings.*

*Based on the model, a quantitative analysis of the credit risk of 302 non-credit record enterprises is carried out and the bank' credit strategy is provided when the total annual credit is 100 million yuan. Finally, this paper comprehensively considers the impact of credit risk and unexpected factors (e.g., the COVID-19) on enterprises, and provides the bank's credit adjustment strategy when the total annual credit is 100 million yuan.*

***Keywords***

*analytic hierarchy process (AHP), BP neural network model, objective return function, risk measurement*

## 1. Presentation of the Problem

The development of enterprises in the 21st century determines to a certain extent the development trend of the national market economy. With the continuous adjustment of China's enterprise policy, a large number of small, medium and micro enterprises have gradually become the mainstay and pillar of China's market economy development. However, most MSMEs rely on single-channel bank financing for their development, which exacerbates the development of MSMEs because of economic instability and high risk (Meng, Li, Dong, & Zhao, 2022). So, the above reasons have led to the reluctance of most financial institutions to lend to MSMEs at their own risk or to restrict MSME lending in various ways. Therefore, the establishment of a more complete and comprehensive credit evaluation system is very important for the development of MSMEs at present.

Authors study the credit strategy for MSMEs by building a mathematical model based on the actual situation and the data information in the annexes to address the following questions:

(1) The credit risk of 123 enterprises with credit records is quantitatively analyzed and credit strategies are proposed.

(2) Based on question 1, a quantitative analysis of the credit risk of 302 non-credit record enterprises is carried out and the bank' credit strategy is provided when the total annual credit is 100 million yuan.

(3) The production and operation mode and economic benefits of enterprises may be affected by some sudden factors, which have different impacts on enterprises in different industries and categories. This paper comprehensively considers the impact of credit risk and unexpected factors (e.g., the COVID-19) on enterprises in Annex 2, and provides the bank's credit adjustment strategy when the total annual credit is 100 million yuan.

## 2. Analysis of the Problem

### *2.1 Analysis of Problem 1*

If question 1 needs to be analyzed, it is necessary to quantitatively analyze the credit risks of 123 enterprises with credit records, and the evaluation of credit risks includes the credit rating and strength of enterprises. Therefore, the following AHP is adopted: credit rating and enterprise strength are used as the first-grade indexes to analyze the second-grade indexes that affect them. After six second-grade indexes are determined: sales growth rate, input growth rate, sales tax, total profit, profit growth rate and sales, the importance weight of each indicator is calculated by the eigenvalue method, and the weight between each level is calculated. Finally, the quantitative analysis of the target (credit risk) is realized (Sreekantha & Kulkarni, 2012). At the same time, the credit risk is classified by quantitative analysis of credit risk, and then combined with the actual situation to determine the loan pricing (amount) and loan interest rates for enterprises with different credit risk levels, such as different lending policies are given to enterprises with excellent, good and medium credit risk levels.

### *2.2 Analysis of Problem 2*

Question 2 assesses the credit risk of 302 enterprises without credit records on the basis of question 1.

First, compared to question 1, since all enterprises do not have credit ratings, the credit ratings of all enterprises need to be rated based on the second-grade indexes affecting credit ratings in question 1 and the data in question 2. Meanwhile, the BP neural network model should be constructed, the above variables are regarded as independent variables, and the credit rating of each enterprise is taken as the dependent variable, and then the model design is completed by determining the training function, setting the input layer (including the number of nodes in the input layer), the output layer, and the hidden layer. In this paper, the neural network model is trained based on the data of 123 enterprises with credit records, and the credit rating of each enterprise is obtained directly. Finally, after the credit rating of each enterprise is obtained, the risk assessment of 302 enterprises is quickly performed to obtain their credit risk rating according to the credit risk assessment model in problem 1.

In the next step, the bank's credit strategy and credit risk level in question 1 are used as the priority lending conditions, and the proposed interest rate (credit strategy in question 1) and default rate of enterprises with different credit risk levels are combined to establish the bank's total target return function with the loan amount of "good" level as the independent variable under the premise of satisfying the demand for "excellent" level loans with the aim of reasonably allocating the total loan amount of 100 million yuan.

*2.3 Analysis of Problem 3*

Analysis of problem 3 should first determine the emergent factors affecting the enterprises. In this paper, the COVID-19 in 2020 is studied as a sudden factor, 302 different types of enterprises are classified, and then the impact of the COVID-19 on enterprises was investigated to recalculate the second-grade indexes of the affected part, the total sales, sales tax and total profit are recalculated according to the degree of influence. Because the unexpected situation cannot directly affect the annual sales growth rate, input growth rate and profit growth rate of the enterprise, the AHP is applied here. On the premise that the first-grade indexes are basically the same as in problem 1, total sales, sales tax and total profit are used as the second-grade indexes, and the importance weights of each level of indicators are recalculated by the eigenvalue method, and then the weights between the levels are calculated. Due to the number of the second grade indexes affecting the reputation level are reduced, the reputation level is replaced by the reputation score to simplify the subsequent calculation.

The credit risk assessment model in Question 2 is used as a basis to modify the primary and the second-grade indexes as described above and to calculate the credit risk score for each enterprise in the case of contingencies. Since the previous indicators have been changed, the correspondence between credit risk scores and credit risk levels should be adjusted to some extent.

Finally, this paper combines the adjustment scheme of bank loan tax rate under the epidemic situation and the credit strategies in problem 1 and problem 2 to reduce the base tax rate and the limit loan threshold to a certain extent. Similar to question 2, this paper establishes the bank's total target return function with the "good" grade loan amount as the independent variable, and allocates the total loan amount of 100 million yuan in a reasonable method.

## 3. Assumptions of the Model

1. When processing the attachments given in the question, it is determined that all invoice flows are true values. So enterprises are abode by the law, there is no tax evasion, tax evasion, concealment, misstatement.

2. When determining the influencing factors of corporate reputation rating, it is found that it has a nonlinear correlation with the selected factors, while ignoring the system error caused by the network itself when using BP neural network to predict the results.

3. When determining the evaluation index of reputation rating, it can be quantified as a number, and this index is only related to the relevant factors mentioned in this paper, while ignoring other factors that are not available in the annex.

4. Ignore the differences among individuals based on big data identification, such as the universality of the impact of the COVID-19 on the same type of enterprise, and all enterprises in the same category are affected to the same extent.

5. In the establishment of the objective function of the total return of bank loans, this paper argues that credit risk rating for “excellent” enterprises will be in accordance with the maximum amount of loans, and the amount of loans for enterprises with other credit risk ratings will be analyzed on this basis.

6. In the establishment of the objective function of the total return on bank loans, this paper believes that banks will prudently issue loans, for example, giving priority to lending to enterprises with good credit risk ratings, although it may result in low-interest returns.

## 4. Description of Symbols

| symbols | Notes |
|---|---|
| $a_i$ | Annual sales (yuan) |
| $b_i$ | Annual input (yuan) |
| $x_1$ | The growth rate of sales |
| $x_2$ | The growth rate of inputs |
| $x_3$ | Total output tax (yuan) |
| $x_4$ | Gross profit (yuan) |
| $x_5$ | Profit growth |
| $x_6$ | Gross sales (yuan) |
| $y_1$ | Comprehensive Index of Enterprise Strength Evaluation |
| $y_2$ | Index of corporate reputation |
| O | Index of credit risk |
| Z | (Total loan amount is $100 million) Total bank’s target return (RMB10,000) |
| W | (Enterprises with different credit risk levels) Bank target return (RMB 10,000) |
| $r_i$ | (Enterprises with different credit risk levels) Bank loan interest rate |
| $A_i$ | (Enterprises with different credit risk levels) The total amount of bank loan |
| $p_i$ | Corporate default rate |

## 5. Establishment and Solution of the Model

### *5.1 Establishment and Solution of Problem 1 Model*

5.1.1 Data Processing

The available and accessible data in Annex 1 of this paper are considered and then the bank's invoice data are combined to process the available data as follows:

1. Since voided invoices are applied to the financial situation of refunds, which cannot measure the indicator of "default rate", all the voided invoices in Annex 1 and Annex 2 are deleted.
2. All company labels in Annex 1 are digitized (e.g., company E1 becomes 1.);
3. The indicator of "credit rating" was quantified, such as 100 points for level A, 75 points for level B, 50 points for level C and 25 points for level D.

Finally, the existing sales invoice tax, input invoice tax, sales invoice amount, and input invoice amount in Annex 1 are used to obtain the sales growth rate $x_1$, input growth rate $x_2$, gross profits $x_4$, and profit growth rate $x_5$ for 123 enterprises respectively using the following formula.

$$x_1 = \frac{a_{2019} - a_{2018}}{a_{2018}} \times 100\% \tag{1}$$

$$x_2 = \frac{b_{2019} - b_{2018}}{b_{2018}} \times 100\% \tag{2}$$

$$x_4 = \sum_{i=2016} a_i - \sum_{i=2016} b_i \tag{3}$$

$$x_5 = \frac{(a_{2019} - b_{2019}) - (a_{2018} - b_{2018})}{a_{2018} - b_{2018}} \times 100\% \tag{4}$$

Given the full reliability of the data, all growth rates are for 2018-2019.

In addition, sales tax $\mathrm{x}_3$ and sales $\mathrm{x}_6$ can be directly calculated by invoice sales tax and sales in Annex 1.

5.1.2 Establishment of Credit Decision-making Model

Firstly, the six evaluation indexes of 123 enterprises are determined: sales growth rate $x_1$, input growth rate $x_2$, output tax $x_3$, gross profit $x_4$, profit growth rate $x_5$ and sales $x_6$. Then, the credit risk of 123 enterprises with credit records is quantitatively analyzed by AHP (Wang & Ieee, 2021). Obviously, the assessment of credit risk includes the credit rating of the enterprise and the strength of the enterprise, both of which are used as First grade indexes in the AHP. 6 evaluation indicators in 5.1.1 are used as the second-grade indexes, as shown in Figure 1.

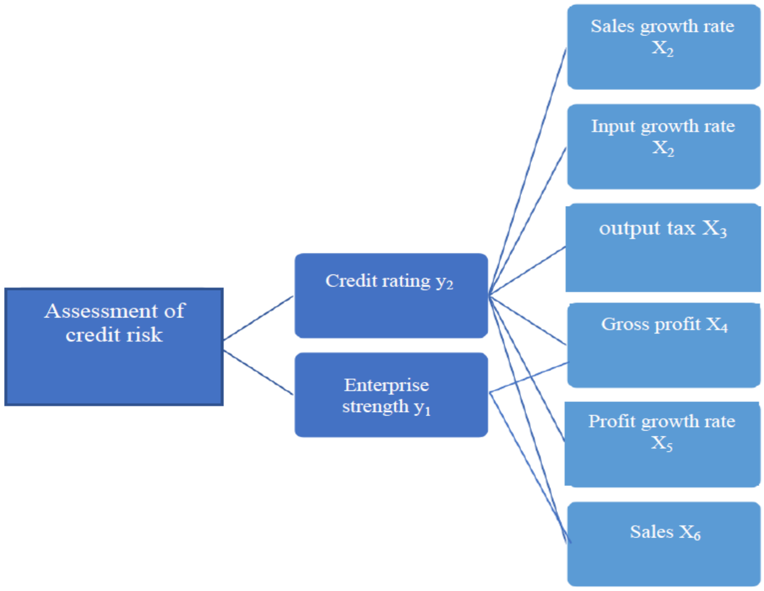


**Figure 1. Hierarchy in Problem I**

The current enterprise credit rating standards are combined with the characteristics of Annex 1 data, and then the sales growth rate $x_1$, input growth rate $x_2$, output tax $x_3$, gross profit $x_4$ and profit growth rate are selected as the evaluation criteria for 123 enterprises in Annex 1 credit rating of the first level indicators, and the sales growth rate, input growth rate, total profit of sales tax, profit growth rate are selected as the evaluation criteria of the second level indicators.

After the primary and the second-grade indexes are identified, principal component analysis is adopted to calculate the weights of each level of indicators. First, the importance weights of the primary and the second-grade indexes are calculated separately, and second, the weight of each factor in the primary and the second-grade indexes is calculated.

Firstly, the judgment matrix between credit risk O and firm strength $y_1$ and firm credit rating $y_2$ is constructed, and secondly, principal component analysis is employed to calculate the weight matrix $\boldsymbol{A}_1$, and the results are shown in Table 1:

**Table 1. O-y Judgment Matrix**

| $O$ | $y_1$ | $y_2$ | $\omega_0$ |
|---|---|---|---|
| $y_1$ | 1 | $\frac{1}{3}$ | 0.25 |
| $y_2$ | 3 | 1 | 0.75 |

The maximum eigenvalue $\lambda_{1max} = 2$ of the matrix $\boldsymbol{A}_1$ is further calculated, and then $CR_1 = 0 < 0.1$ is obtained by the consistency test $CR = \frac{\lambda_{max}-n}{n-1}$ to detect the matrix consistency.

Further, the relationship between firm credit risk, firm strength and firm credit rating is obtained:

$$O = 0.25y_1 + 0.75y_2. \quad (5)$$

Similarly, the judgment matrix $\boldsymbol{A_2}$ between firm strength $y_1$ and the second-grade indexes is constructed, the weight matrix $\omega_1$ and maximum eigenvalues $\lambda_{2max}$ are calculated, and the consistency of the matrix is detected by $CR = \frac{\lambda_{max}-n}{n-1}$.

**Table 2. $y_1$-x Judgment Matrix**

| $y_1$ | $x_6$ | $x_4$ | $\omega_1$ |
|---|---|---|---|
| $x_6$ | 1 | $\frac{1}{3}$ | 0.25 |
| $x_4$ | 3 | 1 | 0.75 |

$$\lambda_{2max} = 2, CR_2 = 0 < 0.1 \quad (6)$$

In summary, the relationship between firm strength, the total profit of enterprises, and firm sales are calculated:

$$y_1 = 0.25x_6 + 0.75x_4 \quad (7)$$

Similarly, judgment matrix $\boldsymbol{A_3}$ between corporate reputation levels $y_2$ and the second-grade indexes $\boldsymbol{A_3}$ are constructed, weight matrices $\omega_2$ and maximum eigenvalues $\lambda_{3max}$ are calculated, and the consistency of the matrices is detected by $CR = \frac{\lambda_{max}-n}{n-1}$.

**Table 3. $y_2$-x Judgment Matrix**

| $y_2$ | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | $\omega_2$ |
|---|---|---|---|---|---|---|
| $x_1$ | 1 | 1 | $\frac{1}{3}$ | $\frac{1}{3}$ | $\frac{1}{5}$ | 0.0758 |
| $x_2$ | 1 | 1 | $\frac{1}{3}$ | $\frac{1}{2}$ | $\frac{1}{3}$ | 0.088 |
| $x_3$ | 3 | 3 | 1 | 2 | 3 | 0.3873 |
| $x_4$ | 3 | 2 | $\frac{1}{2}$ | 1 | $\frac{1}{3}$ | 0.16 |
| $x_5$ | 5 | 3 | $\frac{1}{3}$ | 3 | 1 | 0.2889 |

$$\lambda_{3max} = 5.3325, CR_3 = 0.0742 < 0.1 \quad (8)$$

Finally, the relationship between enterprise reputation level and the second-grade indexes is derived as:

$$y_2 = 0.0758x_1 + 0.088x_2 + 0.3873x_3 + 0.16x_4 + 0.2889x_5. \quad (9)$$

The corporate strength and weight vector of the second grade indexes under enterprise reputation level are obtained by the above calculation process respectively.

$$\omega_1 = [0.75, 0.25]^T, \omega_2 = [0.0758, 0.088, 0.03873, 0.16, 0.2889]^T$$

The weight vectors $\omega_0$ for corporate credit risk, corporate strength and corporate reputation are combined to design the combined weights for each secondary indicator (as shown in Table 4).

**Table 4. Comprehensive Weight of the Second Grade Indexes**

| First-level indicator | Second-level indicator | Comprehensive weight |
|---|---|---|
| Corporate Strength $y_1$ | Sales $x_6$ | $0.25 \times 0.25$ |
| | Gross profit $x_4$ | $0.75 \times 0.25 + 0.16 \times 0.75$ |
| Enterprise credit rating $y_2$ | Sales growth rate$x_1$ | $0.0758 \times 0.75$ |
| | The growth rate of inputs $x_2$ | $0.088 \times 0.75$ |
| | Output tax $x_3$ | $0.3873 \times 0.75$ |
| | Profit growth $x_5$ | $0.2889 \times 0.75$ |

The data information of the six important influencing factors in 5.1.1 is normalized to obtain the item scores of each enterprise. The above data are calculated to obtain the relationship of credit risk scores $v_i$ for MSMEs:

$$S = \sum_{i=1}^{6} \omega_i v_i \tag{10}$$

After the credit risk of each firm is quantitatively analyzed, the credit strategy is usually given differently by each bank according to the credit risk score. In an empirical study of credit asset pricing in commercial banks, researchers have conducted a regression analysis on many factors affecting bank credit pricing and interest rates by constructing a Tobit regression model. The results of regression analysis show that "asset size, asset returns" (i.e., "enterprise strength" studied in this paper) are the main factors determining loan pricing, and "comprehensive credit" (i.e., "enterprise reputation level" studied in this paper) is the main factor determining loan interest rate (Wang & Ieee, 2021).

The following credit strategy is exhibited when the bank's total annual credit is fixed:

The credit risk score of each enterprise is calculated according to equation (10), and then divided into three credit risk levels as shown in Table 5:

**Table 5. Criteria for Classifying Credit Risk Level**

| **Risk rating of corporate credit** | **Risk rating for corporate credit S** |
|---|---|
| **Excellent** | S≥0.2 |
| **Good** | 0.2>S≥0.15 |
| **Average** | S < 0.15 |
| **Credit grade D** | N/A |

Enterprises with a rating of ≥0.2 in the text are identified as trustworthy enterprises (excellent), and banks can lend and give appropriate and preferential interest rate. Enterprises with a rating of ≥0.15 <0.2 are identified as general lending risk enterprises (good), and banks can lend, but large loans need to be considered carefully. Enterprises with a score of <0.15 in the text are identified as enterprises with higher lending risk (medium), which can lend but are not recommended to lend large amounts and raise interest rates appropriately. In principle, banks will not lend to companies with a credit rating of D (non-lending risk score).

The benchmark lending rate of 5.32% is selected according to the pricing level of the loan interest rate for micro and small enterprises in Changzhou City, Jiangsu Province (Yang, Qiao, Huang, Wang, S., & Wang, X., 2021). At the same time, the relationship between the annual interest rate of bank loans and customer churn rate in Annex III (shown in Figure 2) is referred to find the small to a large inflection point of the slope closest to the left side of 5.32% (shown in Figure 3) on the relationship between the annual interest rate of bank loans and customer churn rate of credit rating A for enterprises with "excellent" credit risk rating, and the preferential interest rate is set at 4.65%. If a company's credit risk rating is "medium", the risk rate is set at 6.65% by looking for the smallest to the large inflection point on the graph of the bank's annual loan interest rate versus the credit rating C churn rate (as shown in Figure 4) that is closest to the right side of 5.32%.

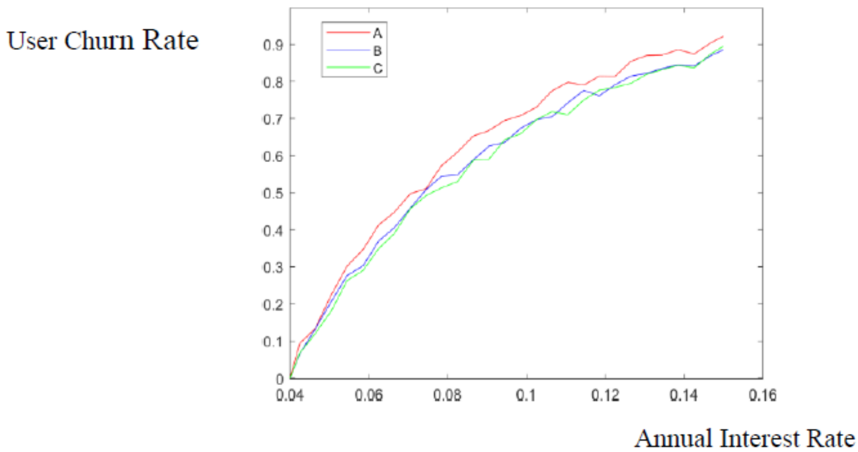


**Figure 2. Relationship between APR of Bank Loans and Customer Churn Rate**

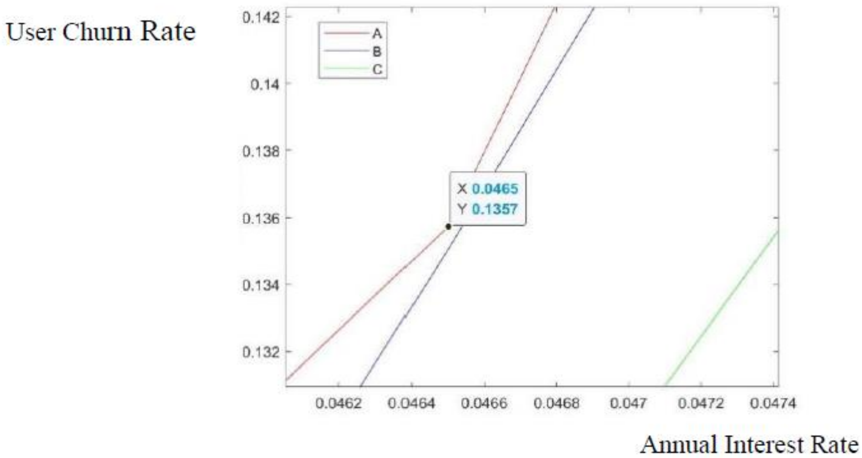


**Figure 3. Preferential Interest Rates for Enterprises with an "Excellent" Rating**

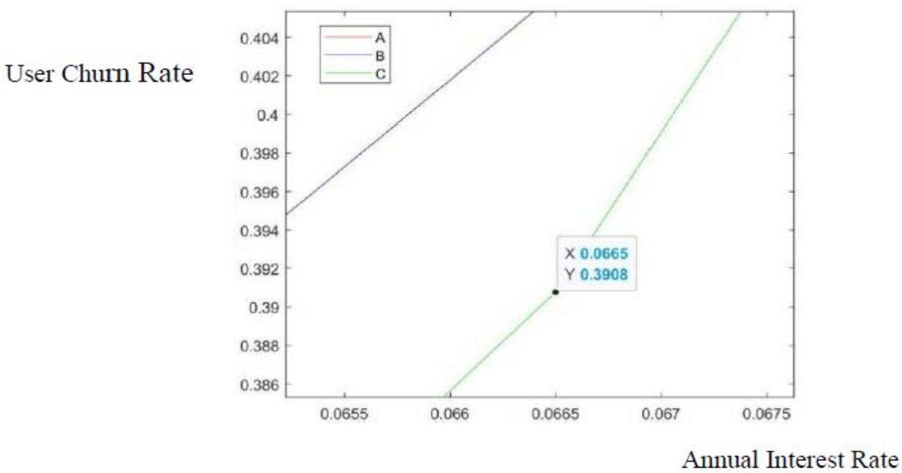


**Figure 4. The Risk Interest Rate for Enterprises with a "Medium" Rating**

Based on the above analysis, when the bank's total annual credit is fixed, the firm's credit strategy is shown in Table 6:

**Table 6. Bank Credit Strategies for Enterprises in Question 1**

| Credit risk level of the enterprise | Loan pricing/recommended loan rates | (Annex 1) Number of enterprises |
|---|---|---|
| **Excellent** | 100,000 – 1 million / 4.65 % | 33 |
| **Good** | 100,000 – 600,000 / 5.32 % | 29 |
| **Average** | 100,000 – 300,000 / 6.65 % | 35 |
| **Credit grade D** | In principle, lending is not recommended | 26 |

*5.2 Establishment and Solution of Model about Problem 2*

5.2.1 Establishment of the Credit Decision Model

First of all, the enterprise entry, sales invoices in annex II are analyzed and processed. The approach is fully consistent with question 1: The growth rate of sales $x_1$, the growth rate of input $x_2$, output tax $x_3$, the gross profit $x_4$, the growth rate of profit $x_5$ and the sales $x_6$ are calculated through the sales invoice tax, the input invoice tax, the sales invoice and the input invoice in annex II.

The missing important indicator in annex II - "corporate reputation rating", combined with the second-grade indexes affecting the reputation rating in question 1 to construct the following BP neural network model:

The second grade indexes affecting the reputation rating are used as input data and normalized to yield the following equation:

$$X = \{x_1, x_2, x_3, x_4, x_5\} \tag{11}$$

The pure linear function is used as the activation function for the input and output layers, and the Sigmoid function is used as the transfer function for the hidden layer.

The input layer is set to 5 neurons, the hidden layer is set to 4 neurons (Gicic & Subasi, 2019), the output layer is set to 1 neuron, and the output values are continuously distributed in the values of [0,100], which can be divided into the following sets of reputation ratings according to the value intervals.

$$Y = \{A, B, C, D\} \tag{12}$$

The data of 123 enterprises with credit records are used as samples to train the BP neural network model, and the credit ratings of 302 enterprises without credit records are predicted based on the processing results of the data in annex II, and the prediction results are shown in Table 7.

**Table 7. Predicting Credit Rating of 302 Companies**

| Credit rating | Number of companies |
|---|---|
| A | 13 |
| B | 124 |
| C | 157 |
| D | 8 |

The data in Table 7 are used as the data for credit rating, then the credit decision model established in 5.1.2 in Problem 1 can be constructed, and then the data in 5.2.1 are normalized to obtain the scores of matching items for each enterprise. Finally, based on the above data, the quantified credit risk score $S$ of SMEs can be obtained:

$$S = \sum_{i=1}^{6} \omega_i v_i \tag{13}$$

**Table 8. Predicting Credit Risk Ratings for 302 Enterprises**

| Corporate Credit Risk Rating | Number of enterprises |
|---|---|
| Excellent | 14 |
| Good | 118 |
| Medium | 159 |
| Credit rating D (Abnormal enterprise data*) | 11 |

*Abnormal enterprise data indicates that the above model is unable to assess the credit risk of the enterprise, so it is not recommended to bank lending in principle.

5.2.2 Establishment and Solution of 100 Million RMB Bank Loan Model

According to the bank's credit strategy for enterprises in 5.1.2, the credit risk level for priority lending as a condition, combined with different credit risk levels of enterprises recommended interest rates $r_i$ to calculate the default rate $p_i$ of enterprises with different credit risk levels:

$$p_i = \frac{Number\ of\ defaulted\ enterprises}{Number\ of\ defaulted\ enterprises} \times 100\% \tag{14}$$

The default rates of enterprises with different credit risk levels are shown in Table 9.

**Table 9. Default Rates of Enterprises with Different Credit Risk Levels**

| The credit risk level of the enterprise | Default rate of enterprises /% |
|---|---|
| Excellent | 0 |
| Good | 2.63 |
| Medium | 5.88 |
| The credit rating D (Abnormal enterprise data*) | Lending is prohibited |

Here the RAROC model (Kanapickiene & Spicas, 2019; Liu, Zhou, & Ieee, 2009) is referred to establish the objective function $Z$ of the total revenue of the bank:

$$maxZ = \sum_{i=1}^{3} W_i \tag{15}$$

Bank returns $W_i$ for all enterprises with the same credit risk rating:

$$W_i = A_i r_i (1 - p_i) - A_i p_i \tag{16}$$

According to the information in Table 8, when the bank's annual loan amount is 100 million yuan, all enterprises that can meet the credit risk level are given the highest amount of loans, so the bank return of enterprises with excellent credit risk rating $W_1$ is:

$$W_1 = 65.1 \tag{17}$$

Set "good" credit risk level enterprise's total loan amount is $x$0,000yuan, for the reputation level of good and medium enterprises, the bank's return $W_2$, $W_3$ are:

$$W_2 = 0.0255x \tag{18}$$

$$W_3 = 32.592 - 0.00379x \tag{19}$$

n summary, the objective function $Z$ of the bank's target total return.

$$Z = 0.021711x + 97.692 \tag{20}$$

Obviously, formula (22) is a quadratic function. When the maximum value $x$ is 70.8 million yuan, that is, the maximum amount of loans per enterprise with a good credit risk level is 600,000 yuan, the maximum objective function is:

$$maxZ = 251.4059 \tag{21}$$

The maximum value of the bank's target total return is 251.4059 million yuan.

*5.3 Establishment and Solution of Model in Problem 3*

5.3.1 Industry Analysis and Data Processing

The irresistible and unexpected factors in society have different impacts on different enterprises, and this question is studied using the Covid-19 as an example. By investigating the big data and then classifying the impact of the epidemic on the enterprises - favorable impact, negative impact and stable transition of the enterprises (almost no impact), the results are shown in Table 10 (Bartik, Bertrand, Cullen, Glaeser, Luca, & Stanton, 2020).

**Table 10. The Impact of the Epidemic on Different Types of Enterprises**

| Degree of impact | Type of business |
|---|---|
| **Favorable impact** | Medical, Culture & Media, Trade & Services, Logistics |
| **The stable transition of companies** | Technology, manufacturing, construction |
| **Negative impact** | Self-employed laborer, food, energy |

The epidemic will directly affect the total sales, sales tax and total profit of the company in the proportion shown in Figure 5.

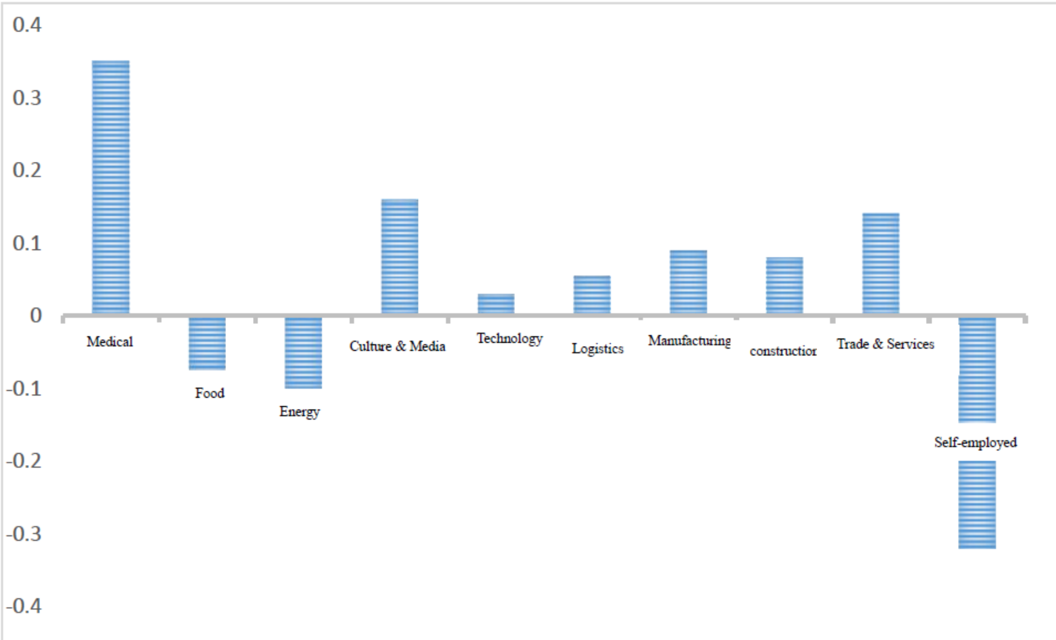


**Figure 5. Proportion of the Impact of the Epidemic on Total Sales, Taxes and Total Profits of Enterprises**

Set the proportion of the impact of the epidemic on the total sales, taxes, and total profits of the enterprises in Figure 5 be $c_i$. The same formula for sales (taxes and total profits) for each enterprise yields the following formula.

$$a'_i = a_i \times (1 + c_i) \tag{22}$$

The epidemic cannot directly affect the annual sales growth rate, input growth rate and profit growth rate of enterprises, so it cannot be used as second-grade indexes to directly affect the first-grade indexes.

5.3.2 Optimization of Credit Decision Model Based on Problem 2

In this paper, the hierarchical analysis method is applied to use reputation score and enterprise strength as the first-grade indexes, and total sales, sales tax and total profit as the second-grade indexes. Among them, total sales and sales tax are used as the second-grade indexes affecting the enterprise strength; sales tax and total profit are used as the second grade indexes affecting the reputation score.

Referring to question 1 here the eigenvalue method is adopted to calculate the weights of each layer of indicators.

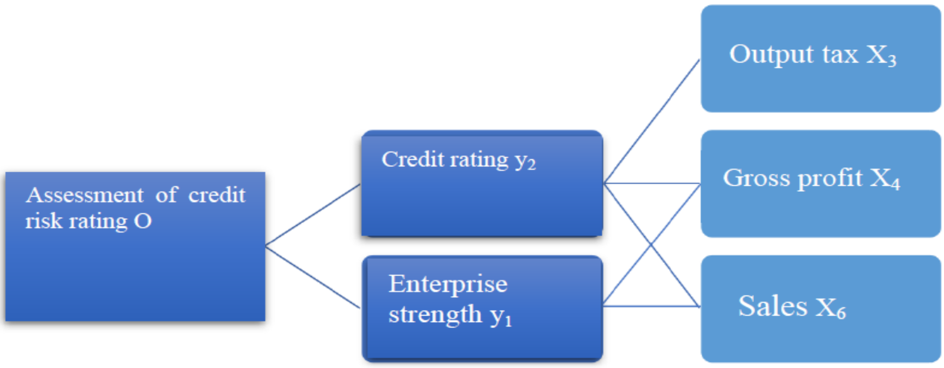


**Figure 6. Hierarchy in Question 3**

Firstly, the judgment matrix $\boldsymbol{A_4}$ between credit risk $O'$ and enterprise strength, the enterprise reputation score is constructed. At the same time, the weight matrix $\omega'_0$ and the maximum eigenvalue $\lambda'_{1max}$ are calculated. And the consistency of the matrix is checked by $CR = \frac{\lambda_{max}-n}{n-1}$.

**Table 11.** $\boldsymbol{O'_2}$**-y Judgment Matrix**

| $O'$ | $y_1$ | $y_2$ | $\omega'_0$ |
|---|---|---|---|
| $y_1$ | 1 | $\frac{1}{3}$ | 0.25 |
| $y_2$ | 3 | 1 | 0.75 |

$$\lambda'_{1max} = 2, CR'_1 = 0 < 0.1 \tag{23}$$

In summary, the relationship between corporate credit risk and corporate strength and corporate reputation score is:

$$O' = 0.25y'_1 + 0.75y'_2 \tag{24}$$

Similarly, the judgment matrix $\boldsymbol{A_5}$ between corporate strength $y'_1$ and its second-grade indexes is constructed, and the weight matrix $\omega'_1$ and the maximum eigenvalue $\lambda'_{2max}$ are calculated, and the consistency of the matrix is checked by $= \frac{\lambda_{max}-n}{n-1}$.

**Table 12.** $\boldsymbol{y'_1}$**-x Judgment Matrix**

| $y'_1$ | $x_6$ | $x_4$ | $\omega'_1$ |
|---|---|---|---|
| $x_6$ | 1 | $\frac{1}{3}$ | 0.25 |
| $x_4$ | 3 | 1 | 0.75 |

$$\lambda'_{2max} = 2, CR'_2 = 0 < 0.1 \tag{25}$$

In summary, the relationship between firm strength and total firm profit and firm sales is:

$$y'_1 = 0.25x_6 + 0.75x_4 \tag{26}$$

Similarly, the judgment matrix $\boldsymbol{A_6}$ between the corporate reputation level $y_2$ and its second grade indexes is constructed, while the weight matrix $\omega'_2$ as well as the maximum eigenvalues $\lambda'_{3max}$are calculated, and the consistency of the matrix is checked by $= \frac{\lambda_{max}-n}{n-1}$.

**Table 13. $y'_2$-x Judgment Matrix**

| $y'_2$ | $x_3$ | $x_4$ | $\omega'_2$ |
|---|---|---|---|
| $x_3$ | 1 | $\frac{1}{3}$ | 0.25 |
| $x_4$ | 3 | 1 | 0.75 |

$$\lambda'_{3max} = 2, CR'_3 = 0 < 0.1 \tag{27}$$

In summary, the relationship between the enterprise strength, total profit, and sales is:

$$y'_2 = 0.25x_4 + 0.75x_3 \tag{28}$$

Combined formula (26), (28), (30), the relationship between enterprise credit risk and its second-grade indexes is:

$$O' = 0.5625x_3 + 0.75x_4 + 0.0625x_6 \tag{29}$$

**Table 14. Comprehensive Weight of Second Level Indicators**

| First-grade indexes | Second-grade indexes | Comprehensive weight |
|---|---|---|
| Business strength$y'_1$ | Sales amount $x_6$ | $0.25 \times 0.25$ |
| | Gross profit $x_4$ | $0.75 \times 0.25 + 0.75 \times 0.75$ |
| Enterprise credit rating $y'_2$ | Output tax $x_3$ | $0.75 \times 0.75$ |

The data processed in 5.3.1 are normalized to obtain the item scores $v_i$ for each enterprise. Combining the above data yields the quantified credit risk scores $S'$ for MSMEs.

$$S' = \sum_{i=1}^{3} \omega_i v_i \tag{30}$$

The relationship between credit risk score and credit risk rating under the epidemic is shown in Table 15.

**Table 15. Criteria for Classifying Credit Risk Levels under the Epidemic**

| Credit risk rating of enterprises | Credit Risk Score of Enterprises S’ |
|---|---|
| **Excellent** | S’≥0.7 |
| **Good** | 0.7>S’≥0.35 |
| **Medium** | 0.35>S’≥0.15 |
| **Poor** | S’<0.15 |

The credit risk rating of 302 enterprises in the credit risk classification standard during the epidemic period is shown in Table 16:

**Table 16. Credit Risk Rating of 302 Enterprises under the Epidemic**

| Credit risk rating of enterprises | Number of enterprises |
|---|---|
| **Excellent** | 29 |
| **Good** | 86 |
| **Medium** | 126 |
| **Poor** | 61 |

Enterprise credit risk level is poor; banks in principle do not handle loan business.

5.3.3 Optimization and Solution of the Model for a Bank Lending RMB 100 Million

Because the default rate could not be updated because of the epidemic impact, which is the same as the establishment of the model in question 2, the default rate is used as the calculated data in question 2.

To encourage the resumption of work and production during the epidemic, most banks lowered their lending rates to some extent, but also adjusted the upper limit of loans to individual enterprises to some extent (Bartik, Bertrand, Cullen, Glaeser, Luca, & Stanton, 2020), as shown in Table 17.

**Table 17. Loan Pricing and Recommended Interest Rate of Banks during the Epidemic Period**

| **Credit risk rating of enterprises** | **Loan pricing/loan recommendation rate** |
|---|---|
| **Excellent** | 100~800 thousand/4.0% |
| **Good** | 100~600 thousand/4.35% |
| **Medium** | 100~300 thousand/5.32% |
| **Poor** | Lending is not recommended in principle |

The RAROC model (Kong, Li, & Ye, 2017; Xia, 2017) is referred to here to establish the objective function $Z'$ on the bank's target total return.

$$maxZ' = \sum_{i=1}^{3} W'_i \tag{31}$$

All enterprises with the same credit risk level, the bank's return $W'_i$ is:

$$W'_i = A_i r_i (1 - p_i) - A_i p_i \tag{32}$$

According to the information in Table 16, in the case of the bank's annual loan amount of 100 million yuan, the bank can meet the credit risk level of all enterprises with the highest loan amount, so the bank returns $W'_1$ about enterprises with excellent credit risk rating are:

$$W'_1 = 92.8 \tag{33}$$

If the credit risk is "good", the total loan amount of enterprises is RMB $x$00,000, then the bank income

$W'_2$ and $W'_3$ of enterprises with a good and medium credit rating are:

$$W'_2 = 0.015x \tag{34}$$

$$W'_3 = 0.01x - 76.8 \tag{35}$$

In summary, the objective functions $Z'$ of the bank's target total return.

$$Z' = 0.025x + 16 \tag{36}$$

Obviously, the formula (38) is the linear function, so when $x$ takes the maximum value of 51.6 million yuan, which is equivalent to all enterprises with good credit risk levels having loaned the maximum amount of 600,000 yuan, the objective function reaches the maximum value:

$$maxZ' = 145 \tag{37}$$

The final maximum value of the bank's target total return is $1.45 million.

## 6. Testing and Evaluation of Models

### *6.1 Test of the Model for Problem 1 and Problem 3*

The credit risk indicators in question 1 and question 3 are the most important. Figure 7 shows that there is a good correlation between credit risk indicators and corporate reputation rating, and the model has good accuracy that showed from the side.

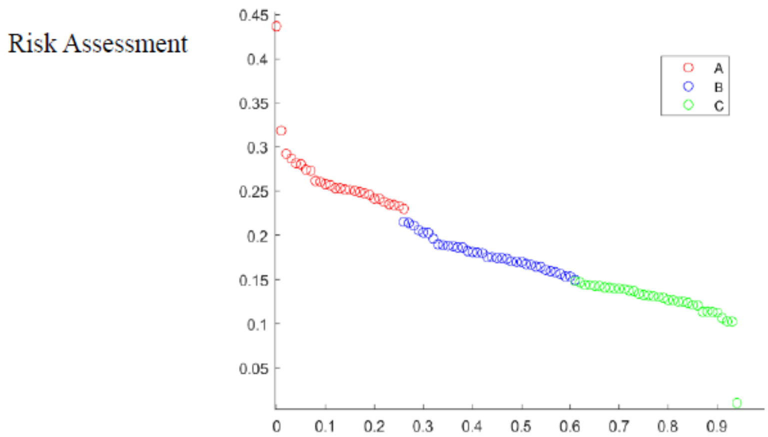


**Figure 7. Relationship between Risk Rating Indicators and Three Types of ABC Credit Ratings Obtained by Hierarchical Analysis**

### *6.2 Testing the Neural Network Model in Problem 2*

As shown in Figure 8, the BP neural network model was trained with a training test ratio of 7:3 to obtain a better rating effect.

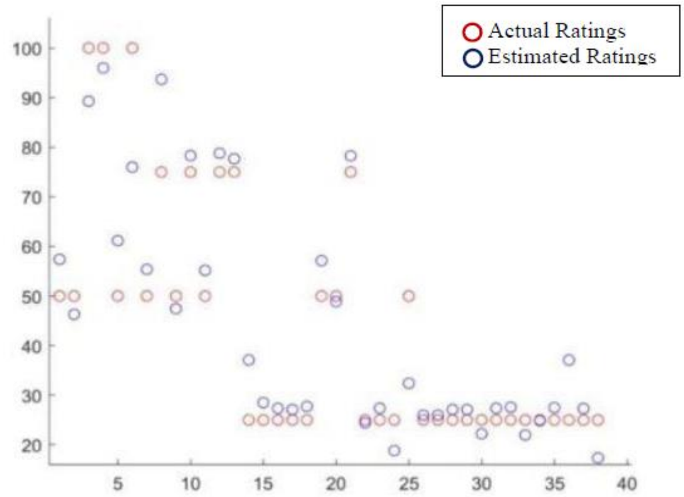


**Figure 8. Relationship between Test Ratings and Actual Ratings in Question 2**

*6.3 Evaluation of BP Neural Network Model*

BP neural network model has the following advantages: large-scale parallel, distributed processing, self-organization, and self-learning. But at the same time, it also has the following shortcomings: high requirements for the typicality of the sample (i.e., sample dependence), slow convergence speed, and structural changes are large and difficult to determine. This requires that relatively representative samples need to be provided when selecting this neural network model because of larger and more dispersed samples, the BP neural network model is difficult to analyze quickly and efficiently.

Because the sample size of this question is large and typical, this allows the BP neural network model to be used as one of the prediction models. Finally, the error between the test result and the actual result is compared by the test result, and the error is within the acceptable range.

## 7. Promotion of the Model

The establishment of the model and the solution of the specific problem in this paper provide a set of methods for a more perfect bank lending evaluation system.

In particular, the above approach is of good generalization value when the data of enterprises are not sufficient (such as this topic, only know the invoice flow of each enterprise), and the modeling and analysis of the only available data give suggestions for banks' lending strategies.

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