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Research article

# Using a genetic backpropagation neural network model for credit risk assessment in the micro, small and medium-sized enterprises

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## ABSTRACT

In China, with the "Double Carbon" goal within reach, Micro, Small and Medium-sized Enterprises (MSMEs) emerge as pivotal contributors to economic advancement. However, they are now confronted with the imperative of transitioning towards green and low-carbon practices. To facilitate the attainment of peak carbon dioxide emissions and carbon neutrality, a refined approach is imperative. This entails precise capital allocation, enhanced financial services, streamlined management, and robust risk mitigation strategies. Consequently, conducting thorough credit risk assessments for MSMEs becomes a crucial endeavor. However, obtaining substantial loans for them proves challenging due to their elusive credit ratings and potential defaults. To address this issue, this study leverages machine learning and intelligent optimization algorithms to construct a classification model for default and credit ratings of MSMEs, utilizing their daily invoice data. Specifically, twelve indicators pertaining to default and credit ratings are extracted. Subsequently, Principal Component Analysis is employed to reduce dimensionality and synthesize all pertinent information. Following this, the Genetic Algorithm-based Back Propagation Neural Network (GA-BPNN) is utilized to delineate the relationship between indicators and default, as well as credit rating, respectively. The results indicate a prediction accuracy of 0.92 for default risk and 0.86 for credit rating. This underscores the efficacy of GA-BPNN in effectively classifying the underlying default risk and credit ratings of MSMEs, offering a promising approach for decision-making.

## 1. Introduction

Since the 1980s, China's Micro, Small and Medium-sized Enterprises (MSMEs) have exhibited significant growth in both enterprise size and the total number of registered companies. They have emerged as a pivotal driving force behind China's economic advancement. According to 2021 statistics, MSMEs, often likened to the 'capillaries' of China's economy, have accounted for 80 % of employment, 60 % of GDP, and 50 % of tax revenue [1]. In the current landscape of the "double carbon" initiative, on September 22, 2020, the Chinese government unveiled its aims of achieving carbon peak and neutrality during the 75th United Nations General Assembly. Following this, on March 5, 2021, China formally incorporated these objectives into the government work report. With the successive rollout of the "1+N″ policies, Micro, Small and Medium-sized Enterprises (MSMEs) find themselves in an unprecedented

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phase of developmental opportunities. Propelled by the rapid expansion of the new energy sector, the financial prowess of mSMEs within this domain continues to grow [2–8]. Unfortunately, based on publicly available information, as of the end of 2021, the documented annual financing requirements for self-employed households nationwide exceeded 2 trillion yuan, yet they received less than 1 trillion yuan in financial support from established financial institutions. This starkly illustrates a yearly financing deficit of 1 trillion yuan. Moreover, loans secured by MSMEs from banking financial institutions constituted merely about 30 % of the total loans extended to enterprises across the board. This discrepancy highlights a glaring imbalance between the number of enterprises and the scale of small and micro economies [9]. Therefore, addressing the pressing issues of high financing costs and accessibility for MSMEs is of more paramount importance.

A majority of MSMEs have operational histories of less than three years, which means they often lack stable, long-term credit records and invoice data. Consequently, the pressing concern in granting credit loans to MSMEs is how to efficiently and accurately evaluate their credit risk [10]. Currently, data mining technology is advancing swiftly, underscoring the heightened significance of data analysis. A wealth of valuable insights can be extracted from the daily operational data of MSMEs [11,12]. By harnessing information technologies like artificial intelligence and machine learning, the gleaned information can be more effectively utilized to yield a more precise reflection of the credit rating and risk assessment for MSMEs. This, in turn, facilitates efficient and accurate decision-making in loan approvals [13]. Numerous researchers have harnessed techniques from the realms of machine learning and deep learning to address the assessment of credit risk in enterprises. These methods encompass SVM, K-means, decision trees, artificial neural networks, and even advanced models like long short-term memory artificial neural networks, yielding commendable outcomes [14,15]. Initially, financial institutions (FIs) turned to supply chain finance (SCF) as a solution for the financing challenges faced by Micro, Small and Medium-sized Enterprises (MSMEs). Consequently, the emphasis on risk assessment has intensified, emphasizing the promising potential of employing machine learning and allied approaches [16].

This study centered on a sample of 123 MSMEs, each possessing a distinct credit history as disclosed by the competition. Due to limitations in data availability as well as the affect of epidemic, only pertinent invoice details from the years 2016–2020 of 123 MSMEs were incorporated into the analysis. Recognizing that the default and credit rating of an enterprise are often intricately linked to its financial strength, this paper defines 12 predictive indicators, encompassing metrics such as upstream and downstream business volume, gross profit derived from invoice information, and more. Subsequently, through correlation analysis, certain indicators with high correlation are pruned, and Principal Component Analysis (PCA) is employed to streamline the dimensionality of the indicators. In the case of the backpropagation neural network (BPNN), the principal components serve as the input variables, while default and credit rating are designated as the output variables. To circumvent potential issues related to local minima in BPNN, training is executed with the aid of a genetic algorithm (GA). Using the GA-BPNN model, an assessment is conducted on small and medium-sized enterprises that may require credit for transformation or low-carbon development between 2016 and 2020. This, in turn, will enable us to offer enhancement recommendations for small and medium-sized enterprises in the midst of transformation and upgrading [14,15,17].

By integrating the strengths of GA and BPNN models, this paper utilizes PCA alongside the GA-BPNN model to assess the credit risk of 123 small, medium, and micro enterprises, effectively addressing the challenges associated with comprehensive evaluation methods and managing a vast array of data indicators. Through a thorough literature analysis, essential indicators such as business volume, gross profit, price tax, coefficient of variation, and others were identified and utilized to develop the GA-BPNN model. The study's findings demonstrate the model's robust stability in credit risk assessment for micro, small, and medium-sized enterprises. Furthermore, the paper provides actionable improvement suggestions for these enterprises, fostering the collection and utilization of operational data for small and medium-sized enterprises to enhance understanding and decision-making.

## 2. Indicators extraction

### 2.1. Data cleaning and preprocessing

The data in this paper are obtained from the database of CUMCM with 123 enterprises in 2016–2020 with. The original dataset is denoted as $A^{(k)}$=($a(k)\ ij$), $B^{(k)}$=($b(k)\ ij$) where $A^{(k)}$ and $B^{(k)}$ indicate the dataset of the input and output invoice information of the $k$th enterprise, respectively. The voided invoices are only used to calculate the voided invoice ratio, and the voided invoices are excluded from the data of other indicators.

### 2.2. Predictors extraction

The credit risk of MSMEs is intertwined with factors such as the enterprise's financial robustness, reputation, and risk mitigation capabilities. Based on recent research, we have identified the following 12 pivotal predictive indicators: upstream business volume, downstream business volume, gross profit, invoice void ratio, input price tax, output price tax, operating duration, average tax rate, number of upstream enterprises, number of downstream enterprises, input variation coefficient, and output variation coefficient [18,19]. The calculation methods for each of these indicators are explicated below.

(1) **Business volume.** It is a critical metric for assessing an enterprise as it provides a snapshot of the overall movement of its assets. A higher business volume indicates a more dynamic capital flow within the enterprise, signifying a healthier economic standing. The combined business volume of both upstream and downstream enterprises encompasses the total number of transactions reflected in the input and output invoices of the enterprise, which are respectively represented by $x(k)\ 1$and $x(k)\ 2$ as follows:

$$\begin{cases} x_1^{(k)} = \sum_{i=1}^{n_k} \left(1 - a_{i7}^{(k)}\right) \\ x_2^{(k)} = \sum_{i=1}^{m_k} \left(1 - b_{i7}^{(k)}\right) \end{cases} \tag{1}$$

where *a(k) i7, b(k) i7*are the input and output invoice status, respectively; 0 and 1 represent non-default and default, respectively.

(2) **Gross profit.** It serves as a key indicator of an enterprise's revenue performance. A higher gross profit signifies a more robust operational performance, and consequently, a reduced risk for the bank in extending loans to the enterprise. Specifically, gross profit is derived by subtracting the total direct cost from the total revenue of the enterprise [18]. This can be calculated as follows:

$$x_3^{(k)} = \sum_{i=1}^{m_k} b_{i4}^{(k)} \left(1 - b_{i7}^{(k)}\right) - \sum_{i=1}^{n_k} a_{i4}^{(k)} \left(1 - a_{i7}^{(k)}\right) \tag{2}$$

where *a(k) i4* and *b(k) i4* are the input and output amount, respectively.

(3) **The voided invoice ratio.** The invoice void ratio represents the proportion of voided invoices in relation to all invoices, serving as an indicator of the reliability of an enterprise's invoicing records. A lower voided invoice ratio indicates a reduced likelihood of errors in the enterprise's invoice data, enhancing the overall credibility of the information. This indicator is denoted as *x(k) 4* and can be calculated as:

$$x_4^{(k)} = \frac{x_1^{(k)} + x_2^{(k)}}{n_k + m_k} \tag{3}$$

(4) **The price tax.** It refers to the sum of the transaction amount and the corresponding tax, providing insight into the capital turnover within the enterprise. A higher total price tax indicates a greater financial strength and robustness within the enterprise. In this paper, the total input and output value tax are denoted as *x(k) 5* and *x(k) 6*, respectively,

$$\begin{cases} x_5^{(k)} = \sum_{i=1}^{n_k} a_{i6}^{(k)} \left(1 - a_{i7}^{(k)}\right) \\ x_6^{(k)} = \sum_{i=1}^{m_k} b_{i6}^{(k)} \left(1 - b_{i7}^{(k)}\right) \end{cases} \tag{4}$$

where *a(k) i6* and *b(k) i6* are the total price and tax of the input and output invoice, respectively.

(5) **Operating time.** Operating time represents the duration since the inception of the enterprise. A longer operating time signifies that the enterprise has endured market trials for an extended period, showcasing its adaptability and stability in response to market conditions [18]. This, in turn, lowers the risk associated with the bank's loan to the enterprise. Operating time is quantified as the number of months from the issuance of the first invoice to the last invoice, which is represented by *x(k) 7* as

$$x_7^{(k)} = \max\left\{ \max_{i\in\{1,\cdots,n_k\}} \left\{a_{i2}^{(k)}\right\}, \max_{i\in\{1,\cdots,m_k\}} \left\{b_{i2}^{(k)}\right\} \right\} - \min\left\{ \min_{i\in\{1,\cdots,n_k\}} \left\{a_{i2}^{(k)}\right\}, \min_{i\in\{1,\cdots,m_k\}} \left\{b_{i2}^{(k)}\right\} \right\} \tag{5}$$

where *a(k) i2* and *b(k) i2* are the date of the input and output invoice, respectively.

(6) **The average tax rate.** This indicator denotes the transaction tendency of the enterprise. A higher average tax rate implies a lower credit risk for larger-scale transactions within the enterprise. The average tax rate can be calculated as follows:

$$x_8^{(k)} = \frac{1}{n_k} \cdot \sum_{i=1}^{n_k} \frac{a_{i5}^{(k)} \cdot \left(1 - a_{i7}^{(k)}\right)}{a_{i4}^{(k)} + a_{i7}^{(k)}} \tag{6}$$

where *a(k) i5* is the tax of the input invoice.

(7) **The number of upstream and downstream enterprises.** This indicator gauges the diversity of business transaction counterparts. A broader array of transaction partners mitigates the risk of potential failures stemming from specific circumstances, thereby reducing overall credit risk. This paper represents the number of upstream and downstream enterprises as $x_9$ and $x_{10}$, respectively.

$$\begin{cases} x_9^{(k)} = \#\left\{a_{i3}^{(k)} \middle| i = 1, 2, ..., n_k\right\} \\ x_{10}^{(k)} = \#\left\{b_{i3}^{(k)} \middle| i = 1, 2, ..., m_k\right\} \end{cases} \tag{7}$$

where *a(k) i3* and *b(k) i3* are the unit code of the seller and buyer in the *k*th enterprise, respectively.

(8) **The coefficient of variation.** This metric quantifies the extent of change in invoice data, providing insight into the variation in the enterprise's monthly transaction amounts. A higher coefficient of variation indicates more pronounced fluctuations in the monthly input amounts, which in turn signifies a less stable supply and demand relationship, consequently increasing the credit risk. It can be calculated as follows:

$$x_{11}^{(k)} = \frac{S_1^{(k)}}{\overline{x}_1^{(k)}}, x_{12}^{(k)} = \frac{S_2^{(k)}}{\overline{x}_2^{(k)}} \tag{8}$$

where *S(k) 1* and *S(k) 2* are respectively the standard deviation of the valid invoice part of *a(k) i4* and *b(k) i4*; *x̅ (k) 1* and *x̅ (k) 2* are respectively the mean of the valid invoice part of *a(k) i4*and *b(k) i4*. The values of each indicator can be obtained, and part of the data is shown in Table 1.

In order to enhance the clarity and emphasis of the original enterprise credit rating data, we have provided detailed descriptions of the credit ratings and default risks within the training dataset. Within the original dataset, enterprise credit ratings are categorized as A, B, C, and D, which are respectively represented as 4, 3, 2, and 1 in this paper. These distinct credit ratings signify variations in corporate creditworthiness, underscoring the importance of their differentiation. Enterprise default risk is delineated as either 'no default' or 'default', denoted as 1 and 0 respectively in this paper. Fig. 1 illustrates the credit rating risks and default risk of MSMEs.

## 3. Models and optimization

### 3.1. Indicator dimension reduction

In this study, the enterprise's reputation level is chosen as the dependent variable, while a selected set of indicators, which have the most significant impacts on the reputation risk of MSMEs, are designated as independent variables for analysis. Initially, a correlation analysis encompassing the 12 indicators was conducted, with the results visualized in Fig. 2.

Notably, the indicators demonstrating a strong linear correlation were the number of upstream enterprises and the total upstream business volume, exhibiting a correlation coefficient of 0.97, along with the total output tax and the total input tax, displaying a correlation coefficient of 0.90. Consequently, the remaining 10 indicators were identified as independent variables, which are as follows: total upstream business volume, total downstream business volume, gross profit, void proportion of total invoices, total input tax, operating duration, average tax rate, number of downstream enterprises, input variation coefficient, and output variation coefficient. Subsequently, a process of normalization and principal component analysis (PCA) is executed, resulting in a reduction of the dimensionality of the remaining indicators to four. This reduction maintains a cumulative contribution rate of over 70 %, as illustrated below:

$$\begin{cases} X_1 = \alpha_1^1 x_1 + \alpha_1^2 x_2 + \alpha_1^3 x_3 + \alpha_1^4 x_4 + \alpha_1^5 x_5 + \alpha_1^6 x_6 + \alpha_1^7 x_7 + \alpha_1^8 x_8 + \alpha_1^9 x_9 + \alpha_1^{10} x_{10} \\ X_2 = \alpha_2^1 x_1 + \alpha_2^2 x_2 + \alpha_2^3 x_3 + \alpha_2^4 x_4 + \alpha_2^5 x_5 + \alpha_2^6 x_6 + \alpha_2^7 x_7 + \alpha_2^8 x_8 + \alpha_2^9 x_9 + \alpha_2^{10} x_{10} \\ X_3 = \alpha_3^1 x_1 + \alpha_3^2 x_2 + \alpha_3^3 x_3 + \alpha_3^4 x_4 + \alpha_3^5 x_5 + \alpha_3^6 x_6 + \alpha_3^7 x_7 + \alpha_3^8 x_8 + \alpha_3^9 x_9 + \alpha_3^{10} x_{10} \\ X_4 = \alpha_4^1 x_1 + \alpha_4^2 x_2 + \alpha_4^3 x_3 + \alpha_4^4 x_4 + \alpha_4^5 x_5 + \alpha_4^6 x_6 + \alpha_4^7 x_7 + \alpha_4^8 x_8 + \alpha_4^9 x_9 + \alpha_4^{10} x_{10} \end{cases} \tag{9}$$

**Table 1**
Part of indicators extracted from invoice information.

| Enterprise code | Enterprise 1 | Enterprise 2 | Enterprise 3 |
|---|---|---|---|
| Total upstream bussiness volume | 3249.00 | 31435.00 | 4367.00 |
| Total downstream bussiness volume | 7886.00 | 11665.00 | 23688.00 |
| Gross profit | −1678862959.24 | 435079409.22 | 518151016.59 |
| Void proportion of total invoice | 0.04 | 0.04 | 0.02 |
| Total input tax | 6637942028.29 | 162487956.62 | 54179352.52 |
| Total output tax | 4698633440.60 | 626295633.94 | 661070278.70 |
| Operation duration | 29496.00 | 30118.00 | 30118.00 |
| Average tax rate | 0.14 | 0.08 | 0.14 |
| Number of upstream enterprises | 437.00 | 3637.00 | 573.00 |
| Number of downstream enterprises | 360.00 | 1611.00 | 136.00 |
| Input variation coefficient | 0.83 | 0.87 | 4.28 |
| Output variation coefficient | 2.24 | 4.91 | 4.61 |
| Credit rating | 4 | 4 | 2 |
| Default risk | 1 | 1 | 1 |

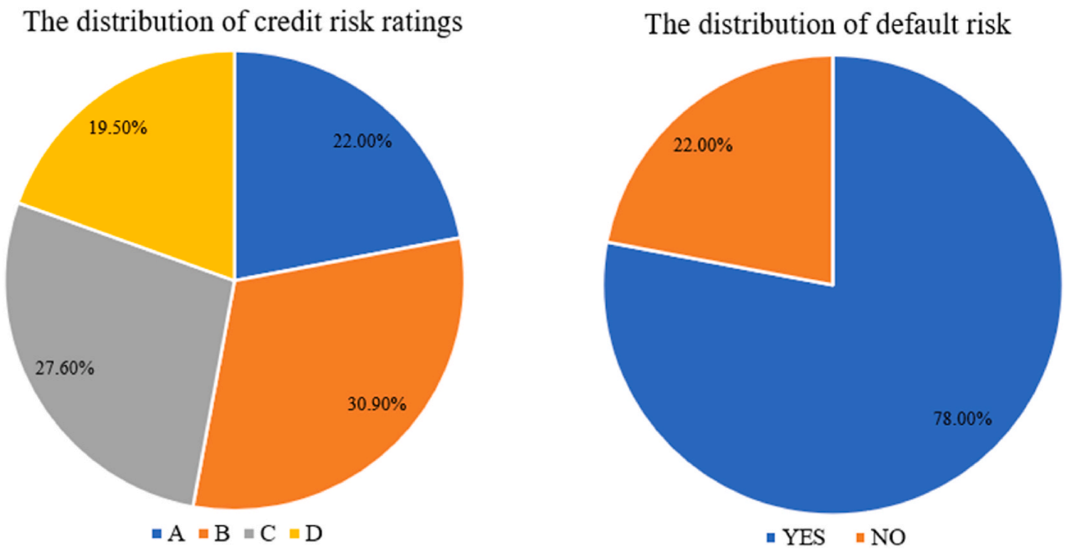


**Fig. 1.** Description of credit rating and default risk of MSMEs.

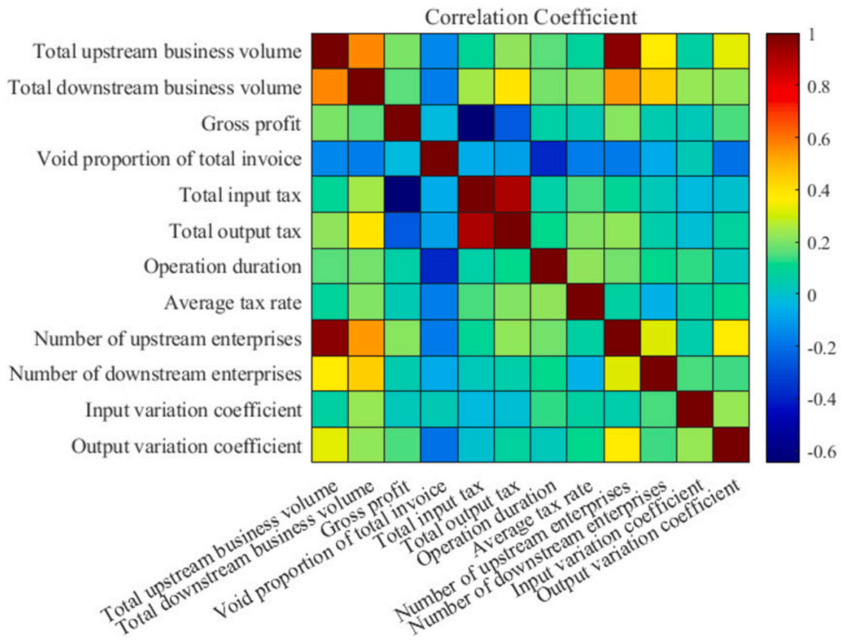


**Fig. 2.** Correlation heatmap of 12 indicators.

**Table 2**
The value of $\alpha q\ p$ ($p = 1, \ldots, 4$, $q = 1, \ldots, 10$).

| $q$ | $p$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| 1 | 0.84 | 0.79 | 0.10 | −0.35 | 0.37 | 0.36 | 0.28 | 0.49 | 0.22 | 0.45 |
| 2 | 0.26 | 0.03 | 0.76 | −0.01 | −0.92 | 0.02 | −0.15 | 0.18 | 0.13 | 0.24 |
| 3 | 0.26 | 0.09 | −0.10 | 0.64 | 0.09 | −0.66 | −0.55 | 0.26 | −0.10 | −0.05 |
| 4 | −0.23 | 0.13 | −0.12 | 0.25 | 0.02 | −0.04 | 0.08 | 0.21 | 0.88 | −0.27 |

where $x_1$, $x_2$, $x_3$, $x_4$, $x_5$, $x_6$, $x_7$, $x_8$, $x_9$ and $x_{10}$ represent the total upstream business volume, total downstream business volume, gross profit, void proportion of total invoice, total input tax, operation duration, average tax rate, number of downstream enterprises, input variation coefficient, and output variation coefficient, respectively. The weight information of the above formula (9) is shown in Table 2.

### 3.2. GA-BPNN modeling

The Backpropagation Neural Network (BPNN) is a simplified computational model inspired by the architecture of biological neural networks [20]. It comprises three layers: the input layer, hidden layer, and output layer. The arrangement of connections between neurons is referred to as the network structure, as depicted in Fig. 3. In the training process of BPNN, the extracted principal components serve as the input, while the company's credit rating and default risk serve as the output.

Within BPNN, neurons are organized into a specific hierarchy to constitute the neural network. Subsequently, the inputs of each neuron undergo a weighting process, followed by summation, and are then subjected to activation functions to produce an output signal. This operational process of neurons can be articulated as follows:

$$\begin{cases} S_j = f\left(\sum_{i=1}^{n} \omega_{ij} X_i + b_j\right) \\ y = g\left(\sum_{j=1}^{m} \omega_{jk} S_j + b\right), \quad i = 1, \dots, n, j = 1, 2, \dots, m \end{cases} \tag{10}$$

where $f$ and $g$ are activation functions; $\omega_{ij}$, $bj$, $\omega_{jk}$, and $b$ represent the weights between the neurons.

Training involves adjusting the connection weights between neurons to bring the entire network's output closer to the desired outcome. While the Backpropagation (BP) algorithm is widely recognized as a prominent neural network learning method, it tends to fine-tune its weights in the direction of local improvement, potentially leading to results confined to local minima [21]. This sensitivity to initial network weights is a notable drawback. Genetic Algorithm (GA), on the other hand, is a parameter search and optimization technique modeled after natural evolutionary processes. Within GA, a population of candidate solutions, or individuals, evolves over successive generations towards an optimal solution. Each generation involves the evaluation of each individual in the population. Those with higher fitness levels are randomly selected for the creation of the subsequent candidate population through biological operations like selection, mutation, and crossover [22].

As the algorithm progresses, the overall best accuracy gradually improves. Typically, the algorithm terminates once either the maximum iteration count is reached or a satisfactory level of accuracy is attained, thereby preventing the individuals of the genetic algorithm from becoming trapped in local minima [23]. In light of this, our study leverages GA to optimize the training process of BPNN. The framework of the combined GA-BPNN model is illustrated in Fig. 4.

This new integrated algorithm can be described in the following two components.

(1) **Determine the BPNN structure:** The input layer comprises four self-extracted principal components, while the output layer is associated with nodes representing the credit rating and default risk. The ideal number of neurons in the hidden layer is determined through a systematic enumeration ranging from 1 to $n$.
(2) **Optimize the weights with GA:** The network weights are encoded as the GA population, and GA is employed to adjust the weights and assess the fitness of each individual. The most suitable individual is determined through a combination of selection, crossover, and mutation operators. The fitness of each individual is determined by the maximum value between the accuracy rate of the training and testing sets, as defined by the fitness function:

$$\text{Fitness} = \max\left\{\frac{x_f}{x_a}, \frac{\widetilde{x}_f}{\widetilde{x}_a}\right\} \tag{11}$$

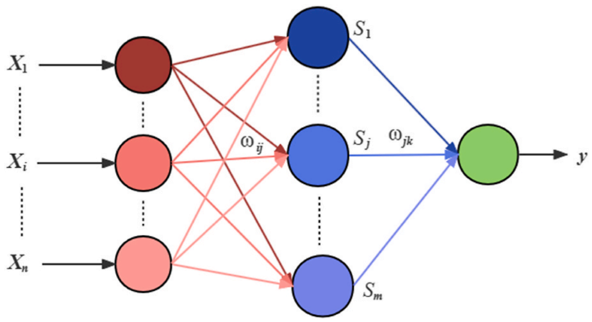


**Fig. 3.** Network structure diagram of BPNN.

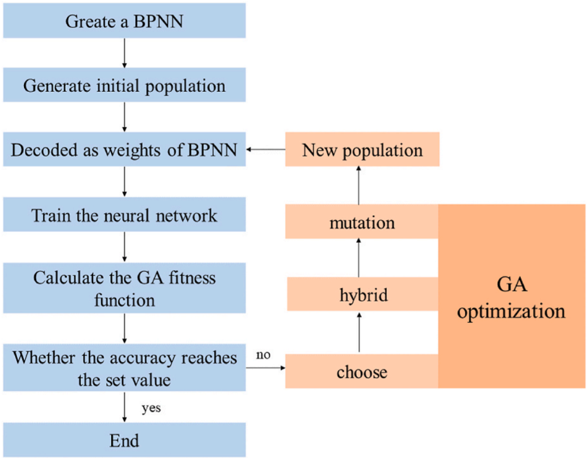


**Fig. 4.** Schematic diagram of GA-BPNN optimization process.

where $x_f$ and $\widetilde{x}_f$ respectively represent the correctly classified number of samples in the training and testing sets; $x_a$ and $\widetilde{x}_a$ respectively represent the total number of samples in the training and testing sets.

## 4. Results

### 4.1. The result analysis by GA-BPNN

In this study, MATLAB 2019b software is utilized to construct a three-layer BPNN for forecasting the default risk based on invoice data from MSMEs. The input comprises the four principal components derived from MSMEs' invoice data, with default risk designated as the output. Given that the number of hidden nodes significantly influences prediction accuracy, it is carefully considered in the model development process [24,25], the most effective prediction results are achieved by varying the predefined number of hidden layer nodes, ranging from 2 to 6. For this study, the sigmoid activation function is applied in both the hidden and output layers. In instances where one class (majority class) may possess significantly more samples than the other (minority class) during the training process, an imbalance arises. To address this, this paper employs the oversampling method [26]. Subsequently, the 10-fold cross-validation technique is implemented to partition the input data into two distinct sets. The relationship between the number of hidden neurons and the corresponding accuracy rates is detailed in Table 3.

Notably, increasing the number of hidden layers notably enhances accuracy for the training set. However, it is observed that an overfitting phenomenon occurs with 5 neurons for the testing set. Consequently, the optimal network structure, featuring 4 hidden neurons, is selected for subsequent prediction. The corresponding weights of the BPNN are calculated and presented in Table 4.

The proposed method is adept at handling binary data. For four-category credit ratings, one approach is to initially split the data into two categories based on the credit rating. Specifically, data with credit ratings A and B are grouped together and labeled as 0 and 1 respectively, while the remaining data falls into another group and is labeled as 2 and 3 respectively. Subsequently, the GA-BPNN model is established for these two coarse-grained classes. This yields an optimal network structure featuring 4 hidden neurons, as demonstrated in Table 5. Concurrently, the associated weights are provided in Table 6.

As previously noted, the GA-BPNN model is suitable for the respective classifications, with results presented in Tables 7–10. In conclusion, the credit rating data can be classified through two distinct processes. The accuracy rates are as follows: 0.922 for the 01–23 credit rating (testing set), 0.943 for the 0–1 credit rating (testing set), and 0.944 for the 2–3 credit rating (testing set).

Upon scrutinizing the predicted and actual default as well as credit ratings for each enterprise, we ascertain an overall accuracy of 0.92 for default prediction and 0.86 for credit rating prediction. Notably, our model correctly distinguishes lower credit rating D from higher credit rating A, and vice versa. It's worth highlighting that companies categorized with credit rating D tend to default, while those with credit rating A do not. These outcomes underscore the superior efficacy and trustworthiness of the GA-BPNN model in

**Table 3**
The impact of hidden neuron count on GA-BPNN default risk accuracy.

| Hidden neurons | Train | Test |
|---|---|---|
| 2 | 0.727 | 0.567 |
| 3 | 0.844 | 0.648 |
| 4 | 0.927 | 0.918 |
| 5 | 0.952 | 0.830 |
| 6 | 0.967 | 0.926 |

**Table 4**
Weights of GA-BPNN model with 4 hidden neurons for predicting default risk.

| $W_1$ | | | | $W_2$ | $B_1$ | $B_2$ |
|---|---|---|---|---|---|---|
| 44.97 | 19.48 | −13.71 | −59.51 | −1016.94 | −23.54 | 0.59 |
| 712.30 | 1082.83 | 156.93 | −299.74 | −409.02 | −264.74 | |
| 179.33 | 650.50 | −45.78 | −313.08 | 808.99 | −503.71 | |
| 34.93 | 13.95 | −11.62 | −48.61 | 597.79 | −15.63 | |

*Note.* $W_1$ and $B_1$ are the weights between the input and hidden layers. $W_2$ and $B_2$ are the weights between the hidden and output layers for the trained GA-BPNN model. Each row corresponds to various hidden layers, while each column corresponds to different X1-X4 indicators.

**Table 5**
The influence of the number of hidden neurons of BPNN on the accuracy of 01–23 credit rating.

| Hidden neurons | Train | Test |
|---|---|---|
| 2 | 0.604 | 0.506 |
| 3 | 0.809 | 0.712 |
| 4 | 0.939 | 0.922 |
| 5 | 0.941 | 0.824 |
| 6 | 0.962 | 0.925 |

**Table 6**
Weights of a GA-BPNN model with 4 hidden neurons for predicting 01–23 credit rating.

| $W_1$ | | | | $W_2$ | $B_1$ | $B_2$ |
|---|---|---|---|---|---|---|
| 19.465 | −58.284 | 7.605 | −20.986 | 132.909 | 43.193 | −119.715 |
| 16.937 | −143.199 | 9.844 | 18.212 | −290.601 | 116.275 | |
| 40.435 | −221.706 | 23.253 | 30.015 | 233.694 | 199.982 | |
| 1.010 | −331.491 | −5.810 | 13.879 | 168.980 | 205.753 | |

classifying credit ratings and predicting defaults.

### 4.2. Comparision with logistic regression model

This paper extensively delves into the daily invoice data of enterprises, extracting indicators tightly linked to default and credit rating. Building upon this, the GA-BPNN model is employed to delineate the intricate quantitative relationships, yielding outcomes that are both effective and dependable. It is worth noting that establishing a quantitative relationship between daily invoice information and default/credit rating based solely on primary invoice data proves to be a challenging task.

$$Y(X) = \frac{1}{1 + e^{-\theta^T X}} = \frac{1}{1 + e^{-(\theta_1 X_1 + \cdots + \theta_4 X_4)}} \tag{12}$$

In this study, a logistic model of Eg.(12) is constructed using the extracted four principal components and the default data, and the corresponding parameters and accuracy metrics are presented in Table 11.

Additionally, a GA-BPNN model featuring 4 hidden neurons is developed, yielding training and testing set accuracies of 0.852 and 0.81, respectively. This indicates that the GA-BPNN model possesses significant predictive capability and robustness. The associated weights are detailed in Table 12.

The Binary Logistic model stands as the predominant choice for examining the relationship between independent variables and classified dependent variables, often serving as the default method for reliability comparisons in enterprise risk assessment. Hence, this study establishes a Binary Logistic regression model utilizing the aforementioned indicators. Remarkably, the accuracy of the Logistic model mirrors that of the GA-BPNN model, underscoring the reliability of the GA-BPNN model developed in this research and its significant predictive efficacy. The endeavors with the aforementioned models illustrate the intricate relationship between daily invoice information and default as well as credit rating. It is often challenging to accurately encapsulate this relationship within a single machine learning model. This underscores the importance of leveraging in-depth data extraction and refining models to effectively describe the quantitative relationship between enterprise primary data and default/credit rating. Consequently, the mathematical model put forth in this paper holds the potential to significantly diminish the data collection efforts for banks, while ensuring an effective and reliable prediction of default and credit ratings.

## 5. Conclusion and discussion

Recently, machine learning technology has found extensive applications in the financial sector, spanning from customer churn

**Table 7**
The influence of the number of hidden neurons of GA-BPNN model on the accuracy of 0–1 credit rating.

| Hidden neurons | Train | Test |
|---|---|---|
| 2 | 0.662 | 0.559 |
| 3 | 0.771 | 0.679 |
| 4 | 0.983 | 0.943 |
| 5 | 0.989 | 0.884 |
| 6 | 0.990 | 0.915 |

**Table 8**
Weights of GA-BPNN model with 4 hidden neurons for predicting 0–1 credit rating.

| $W_1$ | | | | $W_2$ | $B_1$ | $B_2$ |
|---|---|---|---|---|---|---|
| 1.441 | −4.017 | 3.293 | 6.673 | −129.904 | 4.537 | −21.727 |
| 139.121 | 14.576 | 48.382 | −35.436 | 69.600 | 77.568 | |
| −27.776 | −25.364 | 4.881 | 45.873 | 74.246 | 2.297 | |
| −117.886 | 85.092 | 28.097 | 12.783 | 56.371 | 19.228 | |

**Table 9**
The influence of the number of hidden neurons of GA-BPNN model on the accuracy of 2–3 credit rating.

| Hidden neurons | Train | Test |
|---|---|---|
| 2 | 0.654 | 0.550 |
| 3 | 0.825 | 0.811 |
| 4 | 0.969 | 0.944 |
| 5 | 0.971 | 0.843 |
| 6 | 0.982 | 0.907 |

**Table 10**
Weights of GA-BPNN model with 4 hidden neurons for predicting 2–3 credit rating.

| $W_1$ | | | | $W_2$ | $B_1$ | $B_2$ |
|---|---|---|---|---|---|---|
| 7.459 | −27.019 | 8.819 | 27.133 | −78.664 | 26.422 | 21.012 |
| 12.804 | 11.441 | −43.788 | 7.335 | 49.056 | −39.429 | |
| 20.383 | 58.551 | −43.970 | −19.903 | −76.720 | −51.228 | |
| 41.765 | −63.339 | −14.716 | 5.861 | 104.425 | 60.717 | |

**Table 11**
Coefficients and results of the logistic function for predicting default.

| $\theta$ | | | | | Accuracy |
|---|---|---|---|---|---|
| −2.68 | −3.96 | −1.12 | −0.71 | 1.05 | 0.82 |

**Table 12**
Weights of BPNN model with 4 hidden neurons for predicting default.

| $W_1$ | | | | $W_2$ | $B_1$ | $B_2$ |
|---|---|---|---|---|---|---|
| 6.648 | −30.135 | 12.436 | 31.947 | −92.752 | 15.135 | 13.257 |
| 13.625 | 9.823 | −45.245 | 10.586 | 53.256 | −63.256 | |
| 18.427 | 55.623 | −48.056 | −18.246 | −75.569 | −52.563 | |
| 40.633 | −54.821 | −16.198 | 7.357 | 113.567 | 62.156 | |

warnings to anti-fraud measures and credit risk prediction in finance [27–29]. Research on characterizing MSMEs using deep learning has emerged as a prominent area of study. Yet, the application of these advanced technologies often necessitates a substantial volume of training data, which in turn demands significant investments in human resources, materials, finances, and time. Indeed, evaluating the credit default risk of micro, small, and medium-sized enterprises poses a significant challenge in the realm of financing loans [30]. The assessment of enterprise credit encompasses a wealth of data and a diverse array of indicators, underscoring the shortcomings of prior comprehensive evaluation methods in terms of processing capabilities [31]. Hence, dealing with the voluminous datasets associated with these enterprises, the utilization of artificial intelligence for risk prediction emerges as a pivotal and impactful approach [32,33].

The GA-BPNN amalgamates the strengths of genetic algorithms and neural networks, effectively mitigating the inherent non-uniqueness in neural network weights to a significant extent [34]. This study also discerns that this model exhibits a certain degree of proficiency in predicting enterprise risk, offering a potential point of reference for bank loan decision-making. Through the mathematical model established in this paper, banks can utilize daily invoice information to assess the potential default situation and credit rating of an enterprise. This information enables banks to adjust loan interest rates and strategies for MSMEs [34]. For instance, an enterprise with a credit rating of D may be subject to a policy of non-lending, while enterprises with a credit rating of A could benefit from strategies like lowered interest rates and extended credit periods. Given that the enterprise's invoice information is accessible in real-time to national and local taxation departments, it carries legal weight and is often deemed accurate and reliable. Simultaneously, in the assessment of creditworthiness for farmers and the evaluation of credit risk for lenders, the neural network and deep learning demonstrates superior proficiency in handling these tasks, furnishing valuable insights for decision-making [17,35,36].

In the context of the "double carbon" initiative, there has been a growing need for credit among MSMEs to facilitate the transition towards a low-carbon lifestyle [6]. Consequently, the assessment of credit risk for these SMEs has become a pivotal objective within the financial industry. Between 2020 and 2023, and continuing into the future, the introduction of new policies, notably the green credit policy, has expanded the parameters for evaluating creditworthiness within the MSMEs sector. This surge in data volume and the broadening of evaluation criteria have presented challenges, rendering the original credit risk assessment process more complex [37]. Therefore, the integration of genetic algorithms with neural networks for credit risk assessment in small, medium, and micro enterprises shows promise and holds significant exploratory value.

## Data availability statement

The data that support the findings of this study are available on request from the corresponding author upon reasonable request.

## CRediT authorship contribution statement

**Binhao Chen:** Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Data curation, Conceptualization. **Weifeng Jin:** Supervision, Methodology, Formal analysis, Conceptualization. **Huajing Lu:** Software, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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