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Application of QGA-BP Neural Network in Debt Risk Assessment of Government Platforms

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ABSTRACT

How to correctly understand the existence of local government debt, study its risk classification and impact, give full play to the "dual nature" of debt with a full-caliber indicator system, and avoid debt risks to the greatest extent. That is the research direction of this article. In order to improve the accuracy and efficiency of risk assessment and effectively reduce the debt risk of government platform companies, a risk assessment method based on optimized back-propagation (BP) neural network is proposed. First, the method uses quantum genetic algorithm (quantum genetic algorithm, QGA) to adjust and determine the initial weight and threshold of BP neural network and realize the optimization of BP neural network model parameter setting. Then, the QGA-BP debt risk assessment of government platforms is verified that it performs well in the debt risk prediction of government platform companies, and its prediction accuracy and prediction speed are improved.

KEYWORDS

Government Platform Debt, QGA-BP Neural Network, Risk Assessment

INTRODUCTION

Local government debt risk has always been a topic of great concern in China's economic development (Menguy, 2023). In response to such concern, this paper explores targeted measures for effectively controlling local government debt risks and ensuring the sustainable development of the Chinese economy. According to Misra et al. (2023), it is necessary to establish a warning mechanism for local government debt risk in advance. This mechanism can help us better predict the *borrowing repayment risk* of future debts and take corresponding response measures to reduce potential risks. However, in practical operations, predicting debt risk involves complex influencing factors, among which the key influencing factors in the borrowing process are crucial. To address this issue, this article introduces the QGA optimized BP network, a new method applied to government platform debt risk assessment.

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This article verifies the effectiveness of the model through experimental data, and the results show that compared with traditional GA-BP models, the QGA-BP model not only solves the problem of iterative redundancy, but also avoids arbitrary trap problems, significantly improving the accuracy of government platform debt risk assessment. This discovery provides powerful tools and methods for the government in debt management and risk control.

LITERATURE REVIEW

Around 2010, against the backdrop of the complicated international financial environment, China was forced to implement an economic stimulus plan to maintain domestic and international economic and financial stability (Wijayanti et al., 2023). Local governments rely on corporate local financing platforms to expand debt to cope with the impact of economic downturn risks, avoiding the requirement that local governments do not have debt issuance. Under this circumstance, the growth of local debt is accelerating, which is not only concerning to financial regulators and other relevant units, but also gradually gaining interest from academic circles. Based on the gradual development of the subnational debt problem and ongoing research on it, calls for further reforms have grown (Wang, 2023).

A landmark milestone in reforming the problem was the new budget law, which came into effect in 2015 and loosened previous rules that local governments could not carry out debt and bond issuance. This has brought new changes to the structure of Chinese government bonds. That is, debt securitization, in which local governments in China obtain the right to issue bonds and use the bond market to issue local government bonds for financing. In addition, the original debts of local governments have also been gradually cleaned up. For example, debts in the form of bank loans in the past have been replaced with local government bonds. Through systematic local debt clean-up, local debt has shifted from a gray recessive state to an explicit one, which is conducive to the government's comprehensive control and management of debt problems (Honnesh, 2023).

Since the debts of China's central government and local governments have been unified in the form of bonds, the risk assessment that only focused on the central government's debt in the past is no longer suitable for the current new government debt structure (Gubareva & Umar, 2023). Academic research has responded to the new phenomenon of government debt securitization. For example, government debt securitization is gradually included in the research field of government debt risk, which has also maintained such attention in recent studies. When the debt is gradually replaced by bonds, some studies directly use local government bonds as the research subject to analyze government debt risks, but the overall research paradigm is still affected by the traditional research path and does not have any impact on the financial attributes of government bonds and the corresponding risks are examined (Gao & Wan, 2023). However, some studies believe that government bonds, as liquid assets, will have an impact on government debt credit and default behavior (Buthelezi & Nyatanga, 2023).

Recent studies on government debt risk have also incorporated the financial attributes and risks of government bonds into the research framework (Misra, 2023). However, many of these studies focused more on examining debt risk from the perspective of finance than on incorporating the risk of government bonds into the research perspective (Bremer & Bürgisser, 2023). Studies focusing on government bonds as the main body of research often lack financial and other non-financial risk factors. This is related to the research difficulties caused by the insufficient accumulation of data related to local government bonds. However, as the current issuance of local government bonds continues to grow, together with other types of bonds, China's bond market has been pushed to the scale of one trillion yuan (Johnson & Yushkov, 2023). Under the circumstance that the scale of government bonds continues to increase and the operation of government bonds has accumulated relatively sufficient data, now is the right time to systematically investigate the new phenomenon of government debt securitization and, based on the current research theories, incorporate it into the analytical framework of government debt risk research (Kasal, 2023).

MATERIALS AND METHODS

Related Concepts

Local Government

Domestic and foreign literatures have different definitions of the concept of local government. Liu and Bai mentioned that local governments are public organizations within the jurisdiction of national or regional governments that have the power to decide and manage public policies (Liu & Bai, 2023). In the pyramid-shaped government hierarchy, the local government is at the bottom, the national government is at the top, and the middle layer is the intermediate government. From the definition, the local government is under the other two types of government. He et al. pointed out that local governments include local administrative units and states (provinces) other than municipal governments (He et al., 2023). Mura & Donath believed that local governments can be divided into broad and narrow definitions. The broad local government is opposed to government that directly governs a region and its residents, that is, the grass-roots government, and the intermediate government, that is, the regional government, is in between (Mura & Donath, 2023).

Local Government Debt Risk

Regarding the definition of debt, the US Financial Accounting Standards Board (FASB) (1985) believes that a liability is the obligation (Munfaati et al., 2023). Such obligations will result in future sacrifices of expected economic benefits. Based on international accounting standards, Bhattarai et al. define liabilities as the current responsibility of the government for certain past events that result in future losses of government resources in order to obtain certain economic benefits (Bhattarai et al., 2023). The types of debts faced by enterprises, such as credit purchases and financing, are applicable to the government. The total resources owned and controlled by enterprises after deducting debts, that is, net assets for the government cannot be used as owner's equity, but the government. The government serves as the ultimate bearer of any risk that arises, since it has the special status of providing the expenditure responsibility for public goods.

Debt Risk and Its Assessment

Debt risk refers to the potential risk of borrowers being unable to repay the principal and interest of their debts on time. Assessing debt risk determines whether the borrower has sufficient repayment ability and predicts potential default risks in advance (Tang et al., 2023). The following represents some common information about and indicators for assessing debt risk:

- **Borrower credit rating:** Credit rating is an important indicator to measure the borrower's credit status. Usually, professional credit rating agencies evaluate borrowers based on factors such as their financial condition, credit history, and industry prospects, and classify them into different levels, such as AAA, AA, A, BBB, and so on. A higher credit rating indicates that the borrower has good credit and relatively low debt risk.
- **Financial indicators:** Financial indicators can provide quantitative information on the borrower's financial condition. Common financial indicators include the borrower's debt ratio, profit margin, cash flow coverage, etc. These indicators can reflect the borrower's solvency, profitability, and liquidity status, thereby assessing the magnitude of debt risk.
- **Default history:** The borrower's default history is an important reference for assessing debt risk. If the borrower has a history of default in the past, the likelihood of future default is relatively high. Therefore, understanding the borrower's default history can help assess their debt risk.
- **Collateral:** If the borrower provides collateral, such as property or vehicles, these assets can be used as collateral to compensate for losses caused by debt default. Assessing the value and variability of collateral is also an important aspect of assessing debt risk.

When evaluating debt risk, the above information is usually comprehensively considered, and quantitative and qualitative methods are used for analysis and judgment. Specific evaluation methods and models can be selected and established based on actual situations and needs.

In debt risk analysis, common evaluation methods and models include:

- **Traditional rating model:** Traditional rating models are models built based on statistical methods and empirical rules, which quantitatively analyze borrowers' financial indicators, industry data, etc., and provide corresponding credit ratings. Common traditional rating models include, among others, the Altman Z-Score model and the Merton model.
- **Machine learning based rating models:** Machine learning methods have been widely used in debt risk assessment. These models learn a large amount of historical data through training algorithms, enabling more accurate prediction of debt default risk. Common machine learning models include logistic regression, support vector machines, random forests, and neural networks.
- **Neural network-based models:** Neural network models can model debt risk through multi-level nonlinear transformations. These models have strong fitting and generalization abilities and can handle large-scale complex data. Common neural network models include multi-layer perceptron, convolutional neural network, and recurrent neural network.

It should be noted that different evaluation methods and models may differ in terms of data requirements, computational complexity, and explanatory power. Choosing evaluation methods and models that are suitable for actual situations and needs requires comprehensive consideration of factors such as data availability, model interpretability, and reliability. In addition, when assessing debt risk, a comprehensive judgment should also be made based on professional knowledge and experience.

This paper is based mainly on the debt data of a local government, and with the help of the QGA-BP model, the risk level of the region is finally given for decision-making.

Construction of Risk Assessment Model

Risk assessment is actually a classification problem in statistics. A variety of classification models have been developed for risk assessment, and these models can be based on the multivariate statistical analysis method (Gariba & Provazníková, 2023). According to the form of discriminant function and the assumption of sample distribution, the main models are the multiple regression analysis model, the multiple discriminant analysis model (MDA), the logit analysis model, and the nearest neighbor method (Hendiyani & Iba, 2023). Among them, MDA and logit analysis models are the most widely used. The biggest advantage of the statistical model is that it has obvious interpretability, and its primary defect is that its preconditions are too strict.

If the dependent variable is the credit evaluation level, the independent variable consists of some attribute characteristics that affect the credit status of enterprises or individuals, which is:

$$Y = f(x) \tag{1}$$

$$X = \left(x_1, x_2, \cdots, x_n\right) \tag{2}$$

The input in question may be associated with the credit status of enterprises or individuals. Such input involves evaluating the characteristic attributes of the enterprise or individual.

Taking a three-layer network as an example, let X_1, X_2,…, X_n be the network input, and let h_1, h_2,…,h_j be the evaluation value of each feature index, that is, the credit For the evaluation value of risk, the weight but:

$$h_j = f_s\left(\beta_j\right) = f_s\left(\sum_{i=1}^{N} V_{ij} X_i - \varphi_j\right) \tag{3}$$

$$y = f_s(\partial) = f_s\left(\sum_{j=1}^{L} W_j h_j - \theta\right) \tag{4}$$

$$f_s(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

The weights are adjusted through continuous learning and ultimately output when they approach expectations.

Construction of Credit Evaluation Model

Credit evaluation elements include non-numeric data such as gender, marital status, and education level. These data must be converted into different numerical data for each condition according to its impact on credit before it can be used as an input vector. Therefore, it is necessary to first complete the data conversion. For example, for education level, the higher the education level, the more stable the income and the greater the positive impact on credit. Therefore, when converting data, higher education should be converted into a larger value, and low education should be converted into a smaller value.

O=(o_1, o_2,…, o_l), which is closed for the real number field R to [0,1]. It is a non-decreasing continuous function of the set, which represents a neuron model with continuous state.

Take housing conditions, occupation, number of years employed, job title, professional title, annual income, whether to open a bank account, loan history, monthly repayment/monthly income W= (w_1, w_2, w_3).

For the hidden layer there are:

$$y = f\left(\sum_{i=1}^{14} v_{ij} x_i\right) \tag{6}$$

For the output layer there are:

$$o_1 = f\left(\sum_{j=1}^{5} w_{j1} y_j\right) \tag{7}$$

where f(x) is the transfer function. Equations (6) and (7) are personal credit scoring models.

According to the BP algorithm, the weight adjustment formula of the model is obtained as:

$$\text{”}\, w_{j1} = \eta\left(d_1 - o_1\right)\left(1 - o_1\right) o_1 y_j \tag{8}$$

For each input sample, the corresponding Δw_{j1} and Δv_{ij} are calculated, and the weight adjustment formula is obtained:

$$w_{j1} \Leftarrow w_{j1} - \text{”}\, w_{j1} \tag{9}$$

When the errors of o_1 and d_1 reach the required accuracy, the algorithm stops and the learning process ends.

However, in the above learning algorithm, η is selected by experience and cannot be accurately determined, and it usually takes many trainings to find a suitable η.

QGA-BP Neural Network Model

The Quantum Genetic Algorithm (QGA) is an optimization algorithm that combines quantum computing and genetic algorithm. It is based on the principles of quantum computing and the evolution process of genetic algorithms, aiming to improve the efficiency of search and optimization problems by simulating the characteristics of quantum bits (Estefania-Flores et al., 2023). Traditional genetic algorithms solve problems by simulating evolutionary processes in nature. It includes operations such as selection, crossover, and mutation, continuously optimizing the quality of solutions by manipulating an individual's genome. The quantum genetic algorithm introduces concepts such as qubits and quantum gates to represent the solution space of the problem in the form of quantum states. In quantum genetic algorithms, candidate solutions are encoded as qubit states. Quantum bits can be in the superposition state of multiple states, which means that a candidate solution can be in multiple states simultaneously, thereby expanding the search space. By applying quantum gate operations, unitary transformations can be performed on qubits to achieve solution evolution and optimization.

The backpropagation (BP) algorithm is a commonly used neural network training algorithm (Quispe-Adauto et al., 2023). It calculates the error between the predicted output and the actual output and propagates the error back to various levels in the network, thereby adjusting the weights and biases in the network to minimize the error and achieve the goal of training the neural network. The basic idea of the BP algorithm is to use the gradient descent method to update the weights and biases in the network. The key of the BP algorithm is to adjust the weights and biases in the network through error backpropagation. During the backpropagation process, the error is propagated forward layer by layer using the chain rule, thereby calculating the error term for each neuron. Based on the error term and learning rate, each connection weight can be updated to gradually approach the actual output of the network. It should be noted that the BP algorithm is usually used to train multi-layer feedforward neural networks, including input layer, hidden layer, and output layer. In addition, in order to improve the convergence speed of the algorithm and avoid local optima, batch gradient descent or stochastic gradient descent are usually used to update weights and biases.

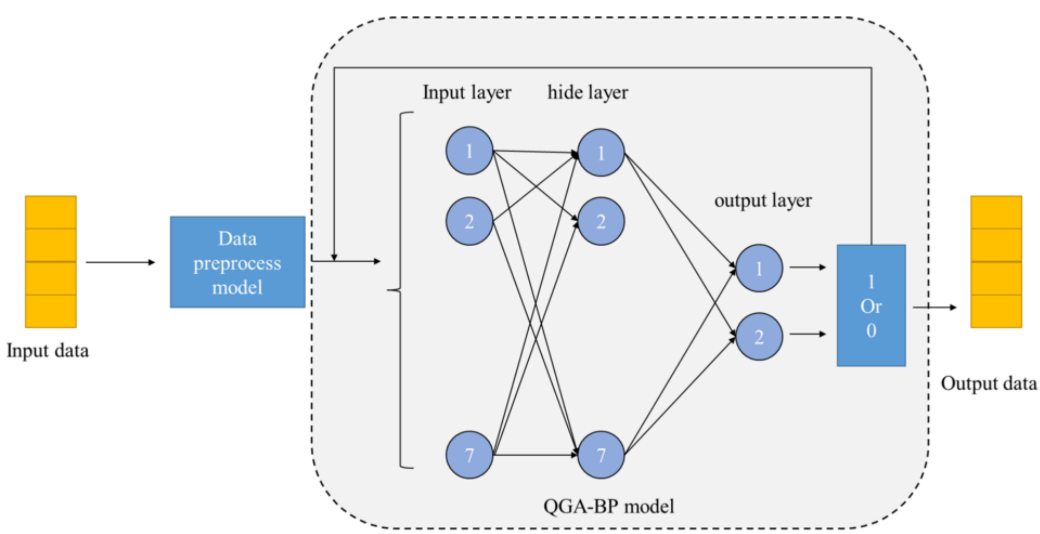
The QGA-BP algorithm is an artificial neural network training algorithm that combines the quantum genetic algorithm (QGA) and backpropagation algorithm (Kussainov et al., 2023). The traditional BP model has problems such as gradient vanishing and gradient explosion during the training process, which leads to slower convergence speed or even inability to converge (Yamin et al., 2023). In addition, BP models are prone to falling into local optima and cannot find global optima. To address these issues, the QGA-BP model uses the quantum genetic algorithm to optimize the weights and bias values of the BP model. The quantum genetic algorithm is a genetic algorithm based on quantum computing, which uses qubits to represent candidate solutions and evolves through quantum gate operations. Specifically, the QGA-BP model encodes the weights and bias values of the BP model into a qubit string and optimizes it using the quantum genetic algorithm. By using qubits to represent weights and bias values, the QGA-BP model can avoid gradient vanishing and exploding problems in traditional BP models and can better avoid falling into local optima. In addition, the QGA-BP model also uses an arbitrary trap escape mechanism to further improve the performance of the model. Arbitrary traps refer to random noise that occurs during the training process, which may cause the model to fall into local optima. The QGA-BP model avoids this situation by introducing a random jump out mechanism. Specifically, the QGA-BP model randomly selects some weights and bias values for modification during the training process to help the model escape any traps. Therefore, this model has better performance and stability compared to traditional BP models. The QGA-BP algorithm combines the global search ability of the quantum genetic algorithm with the local search ability of backpropagation algorithm to find the optimal solution faster, thereby accelerating the speed of model training. Moreover, this algorithm can effectively handle noise and outliers in the data, making the model more robust and reliable when facing complex debt data. In addition, the QGA-BP algorithm can generate clear and easily understandable model structures and parameters, enabling users to better understand the prediction results of the model and adjust and optimize them as needed. Therefore, the QGA-BP algorithm can be applied to various types of debt analysis problems, such as credit rating, default probability prediction, and financial risk assessment. It has high flexibility and adaptability, and can help users evaluate debt risk more accurately, thus making wiser decisions.

The model first involves data preprocessing, which is the process of processing and converting raw data before training a neural network. The specific steps include data cleaning, feature selection, feature scaling, and data balancing. This article uses standardization for data preprocessing, which is a commonly used data preprocessing technique used to unify the numerical range between different features to eliminate deviations caused by different feature scales. Standardization can distribute data in a standard normal distribution with a mean of 0 and a standard deviation of 1. Next, the data is analyzed through convolutional operations, and the analyzed data is compared with the correct results to calculate errors and adjust weights. If it is consistent with expectations, the output layer outputs 1 and stops training. If not, continue iterative training occurs until the output layer outputs 1. The structural diagram of the QGA-BP neural network is shown in Figure 1.

This state can be simply understood as an overlapping state, like a state where multiple qubits exist simultaneously. Quantum bit encoding is a method of encoding classical information into quantum bits. In quantum computing, information typically exists in the form of qubits, while qubit encoding is a technique that converts classical information into qubits. By encoding quantum bits, we can store classical information in quantum bits and utilize the properties of quantum mechanics for processing and transmission. The specific method is to label quantum chromosomes using quantum state vectors and qubit encoding. During the labeling process, each chromosome is updated through the corresponding quantum rotation gate, which can be seen as the evolution of the population to find the optimal individual position. In this way, we can avoid the impact of computational errors on qubit encoding and eliminate negative effects such as noise. In short, this method utilizes the characteristics of quantum mechanics, allowing us to better handle complex computational problems and obtain more accurate results.

In order to overcome the problem of traditional methods easily falling into local optima, this article uses QGA to optimize the weights, so that the output values of the model are as high as possible, in order to find the optimal solution. The process is as follows:

Figure 1. QGA-BP neural network structure diagram



1. Initialize the population $Q(t_0)$. Suppose the population all qubits is m. $Q(t_0) = \{q_{t1}, q_{t2}, q_{t3}, \cdots, q_{tn}\}$, where q_{ti} represents the i-Th individual of generation t. All qubit codes $(\alpha, \beta)^T$ of individuals of the population are initialized to 0.
2. Record the identified population p_{ti} represents the t-Th measurement of individuals in the t-Th generation, expressed as a binary string, The length is m.
3. Set the squares of errors to be $E = \sum_1^n (E_i)^2$, E can be obtained after processing the dataset in the sample training set.
4. Computation is completed immediately when the desired maximum number of iterations is met or the sum of squared errors is less than the specified precision.
5. If the algorithm cannot dynamically adjust according to changing individual and disaster strategies to obtain the next generation of new populations, then the algorithm may not be able to successfully optimize the problem.
6. Increase the disaster strategy, so as to obtain a new one.

The BP network is a kind of feedforward neural network. A feedforward neural network is a typical hierarchical structure—that is, after the information enters the network from the input layer:

$$f(x) = \frac{1}{1 + \mathrm{e}^{-x}} \tag{10}$$

The error at the output of the j-Th element node:

$$E_k = \frac{1}{2}\sum_{k=1}^{n}\left(y_{jk} - T_{jk}\right)^2 \tag{11}$$

Total error:

$$E = \frac{1}{2N}\sum_{k=1}^{N} E_k \tag{12}$$

In the formula, O^1_{jk} means that on the middle is:

$$O^1_{jk} = f\left(\sum W^1_{ij} x_j\right) \tag{13}$$

In the formula: O^2_{jk} means that on the output:

$$O^2_{jk} = f\left(\sum \mathrm{w}^2_{ij} O^1_{jk}\right) \tag{14}$$

In the formula: w_{ij} is the weight from the middle layer to Correction weight:

$$w_{ij} = w_{ij} + \mu \frac{\partial E}{\partial w_{ij}} \tag{15}$$

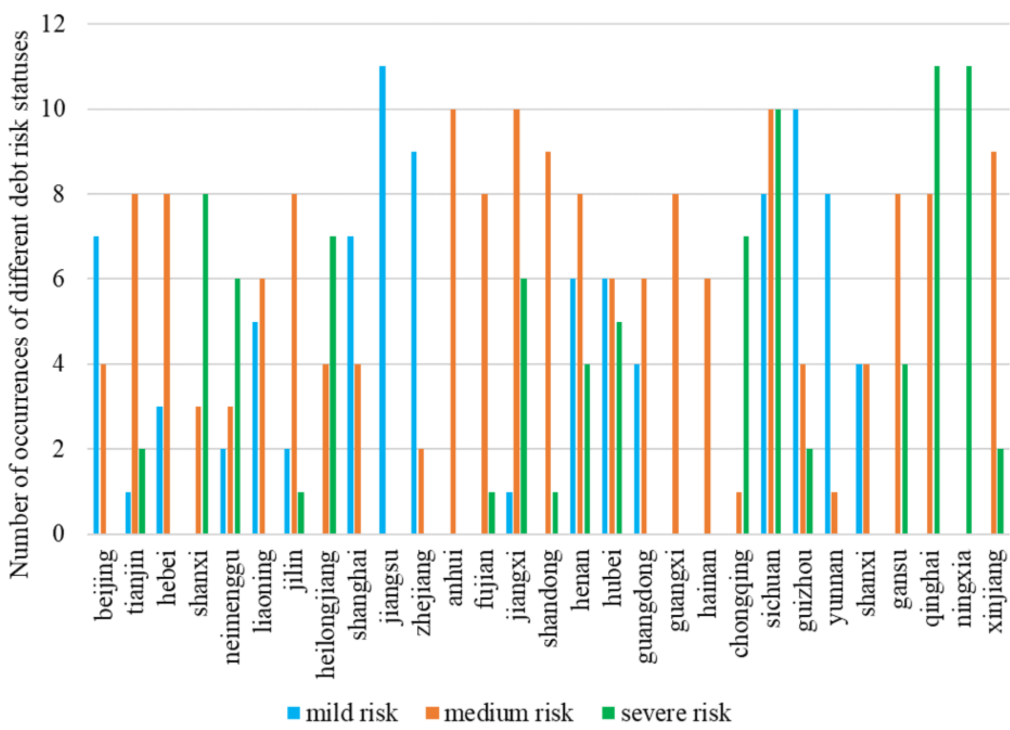
RESULTS AND ANALYSIS

Calculate the Output Sample Value of the Comprehensive Risk of Local Government Debt

This article proposes a QGA-BP neural network model that combines quantum genetic algorithm (QGA) and backpropagation (BP) by introducing a probability evolution mechanism and applies this model to the ongoing debt risk assessment of government platforms. This article will use the government debt risk situation obtained from the website of the National Bureau of Statistics from 2006 to 2020 as statistical data. It can be seen from the previous steps of constructing the early warning system that after setting the debt risk early warning input and output index system, it is followed by the calculation of the debt risk early warning output sample value based on the output index system. On this basis, the number of comprehensive debt risk statuses in 30 provinces from 2006 to 2016 can be counted, as shown in Figure 2 (Leng et al., 2023).

On the whole, during this period, the provinces were in mild risk state 93 times, accounting for 28.18%; in medium risk state 156 times, accounting 47.27%; and in severe risk state 81 times, accounting for 24.55%. The overall debt risk of most provinces is at moderate or above, indicating that the overall risk of local government debt in 2006-2016 during the "Eleventh Five-Year Plan" and "Twelfth Five-Year Plan" period is generally high. From the perspective of different regions, the comprehensive debt risk status of most provinces in the eastern region is generally lower than that of the central and western regions, and the risk status is mainly mild to moderate. Beijing, Hebei, Shanghai, Jiangsu, Zhejiang, and Guangdong have not experienced a serious risk state in the past 10 years. The debt risk status of the central and western regions is basically the same. The central region is mainly in the moderate risk state, and the western region has more severe risks than the central region, with

Figure 2. The number of comprehensive risk status of local government debt in 30 provinces in China from 2006 to 2016



a larger proportion. Some provinces are all in the severe risk state, such as Qinghai and Ningxia. Although the debt scale of the eastern region is relatively large, due to its large economic carrying capacity and strong financial solvency, China's local government debt risks are more concentrated.

The sample data of the above-mentioned early warning input indicators from 2006 to 2019 in various provinces are imported into the QGA-BP neural network trained above, and the comprehensive risk forecast from 2017 to 2020 can be predicted. The specific situation is shown in Figure 3.

From the forecast results shown in Figure 3, the overall trend is a slight increase, but the regional differences are still obvious and China's local government debt risk is still concentrated. The comprehensive debt risk status has changed from a light to moderate risk status to a medium risk status, and the growth rate of the predicted value of the debt comprehensive risk has slowed down. In the central region, the debt comprehensive risk status is still moderate. In the western region, the development of comprehensive debt risk presents completely different characteristics from those in the central and eastern regions. In terms of comprehensive debt risk status, most provinces still have a severe risk status, and the risk status of each province is basically stable. Except for Sichuan, the rest of the western provinces are showing a rapid growth trend. Among them, Guizhou, Chongqing, Yunnan, and Shaanxi have comprehensive debt risk prediction values with an average growth rate of over 7%.

Analysis of the Causes of the Growth of Government Debt

After the reform of the tax-sharing system, local government revenue fell sharply, but expenditure rose instead. One reason for the growth of government debt is that after the reform of the tax-sharing system, local government revenue fell sharply but expenditure rose. Another important reason is the acceleration of urbanization in China. The development of urbanization will firstly lead to the growth of local governments themselves (to cope with the workload of government affairs and governance).

Figure 3. Comprehensive risk forecast of local government debt in 30 provinces in China from 2017 to 2020

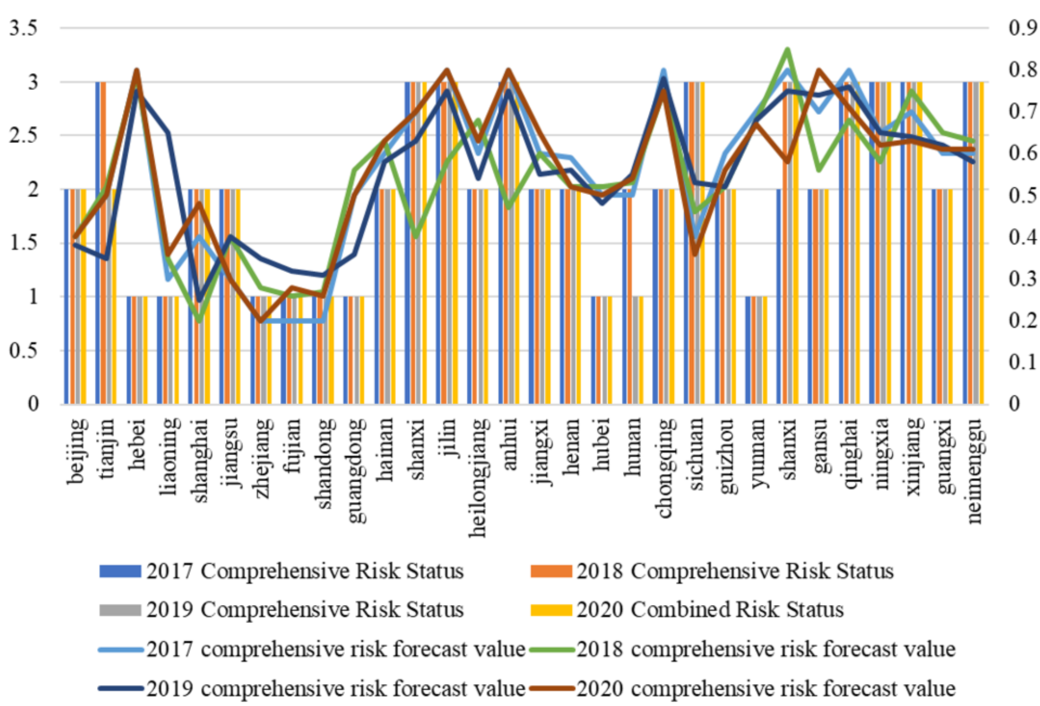


Figure 4 presents the urbanization process in China, with the urbanization rate marked on the right axis. It can be found that China's urban population has been increasing. Both the urbanization rate and the urban population turned upward from around 1995, and the growth rate accelerated.

Migrant workers basically live in cities and towns for most of the year, and although they are not counted as urban populations, in 2001 they numbered over 100 million and some of them also bring their families to work in cities. Migrant workers and their families do not live in a vacuum but rather occupy physical space and have public service needs. After adding the number of migrant workers to the urban population, the adjusted urban population and the adjusted urbanization rate are obtained, which are arranged in Figure 5, where the right axis is the population and the unit is ten thousand people.

A total of six data points in 2021 are selected, and the spreads between local are sorted into Figure 6. The maturity is five years, and both AAA-rated data. It can be found that the interest rate of local government bonds and government bonds was very close in the early days, with a gap of only 30 basis points, while the urban investment bonds at that time had an interest rate difference as high as 160 basis points.

However, based on the above data, the interest rates are gradually converging. It can be considered that the current interest rate marketization is successful in stages; in other words, the yields of different bonds (including local government bonds) reflect the market. The judgment of its risk also aligns with the public and scholars' understanding of the difference in risk of different bonds.

Analysis on the Application of QGA-BP Model

Bank Debt Risk Management

Suppose we consider a bank as a creditor and need to manage the risks in its debt portfolio. Traditional risk management methods may include assessment and prediction based on statistical models, but these methods may not fully consider complex nonlinear relationships and potential arbitrary traps. In this case, the QGA-BP neural network can be applied to debt risk management to provide more accurate and targeted risk assessment and warning mechanisms. The specific operation is as follows:

Figure 4. China's urbanization process

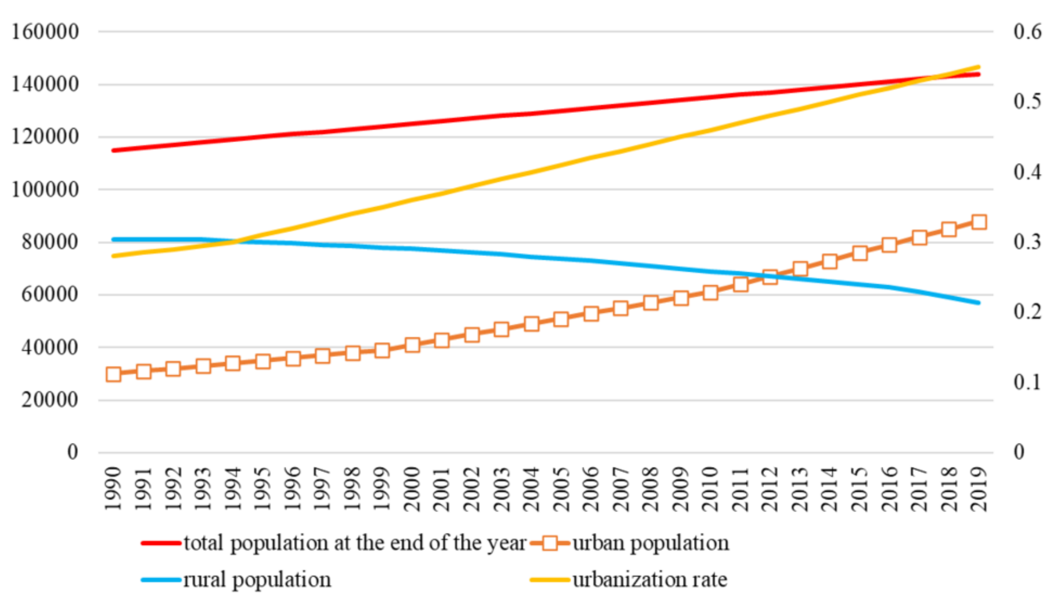


Figure 5. Adjusted urban population and urbanization rate

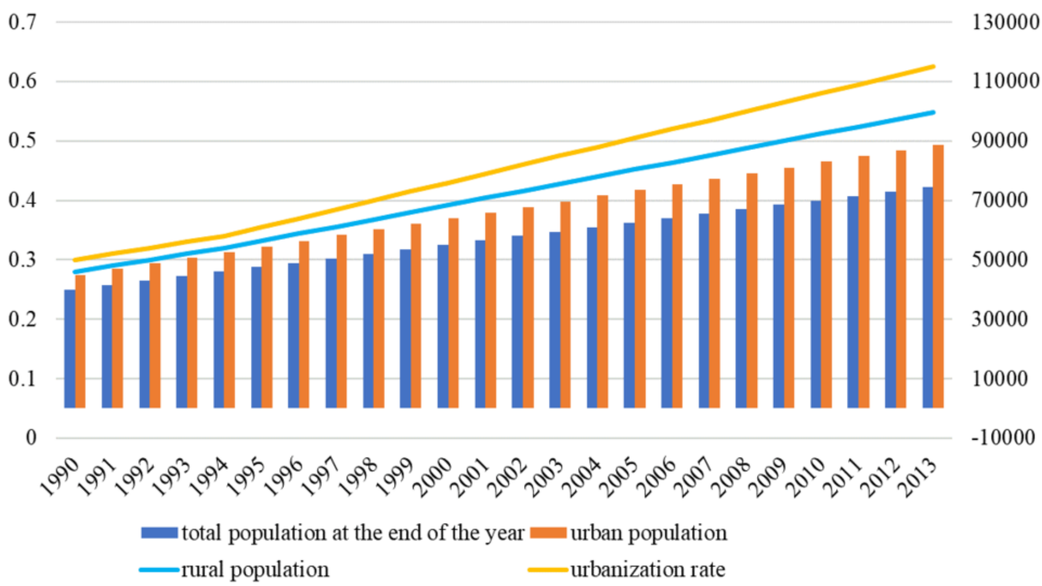
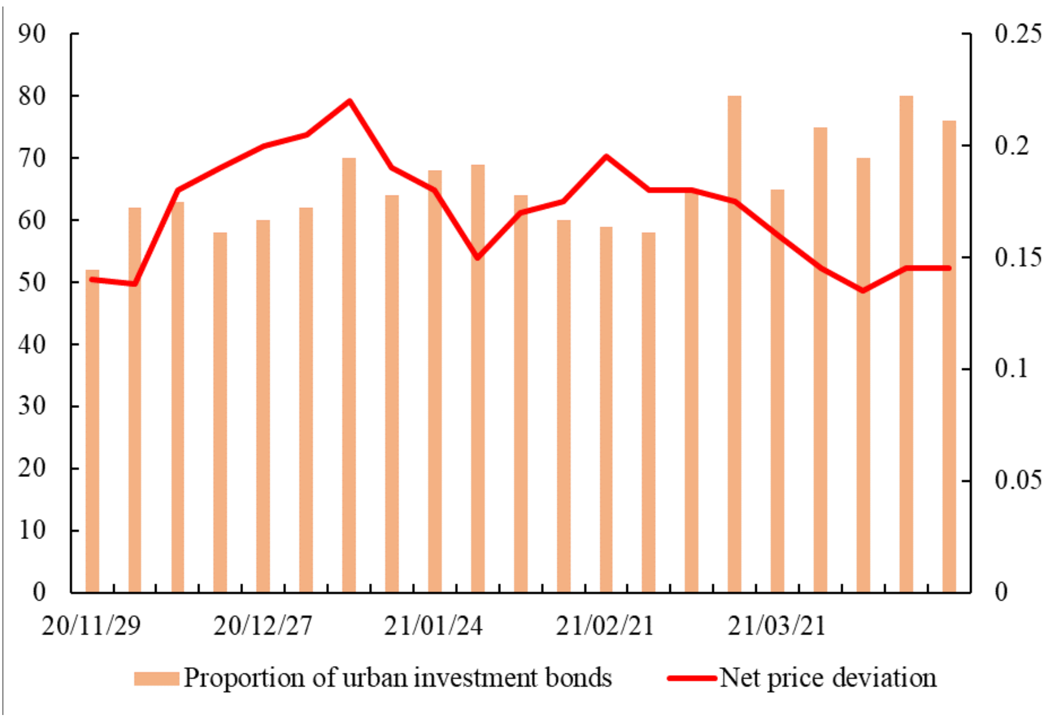


Figure 6. Changes in the spread of urban investment bonds and local government bonds



1. **Data collection and preprocessing:** Firstly, banks need to collect relevant debt data, including borrower's personal information, financial status, repayment history, and so on. Then, they must

preprocess the data, including steps such as data cleaning, feature selection, and standardization, to ensure the accuracy and consistency of the data.
2. **Model training and optimization:** Next, use the QGA-BP neural network to model and predict debt risk. By using the borrower's personal information and financial status as inputs, the QGA-BP model can learn complex nonlinear relationships and predict the probability of debt default. During the training process, the QGA optimization algorithm is used to optimize the weights and biases of the neural network to improve the accuracy and stability of the model.
3. **Risk assessment and warning mechanism:** Based on the trained QGA-BP model, banks can conduct risk assessments on new borrowers and generate corresponding risk warnings. When the model predicts a high probability of default for a borrower, banks can take corresponding measures, such as adjusting loan interest rates and requiring collateral to effectively manage debt risk.
4. **Continuous monitoring and updating:** Debt risk is a dynamic process that requires continuous monitoring and updating of models. Banks can regularly collect new debt data and use this data to retrain and optimize the QGA-BP model to ensure its accuracy and adaptability.

Through the above case study, we can see the application of the QGA-BP neural network in bank debt risk management. It can provide more accurate and targeted risk assessment and warning mechanisms by learning complex nonlinear relationships and using QGA optimization algorithms, helping banks effectively manage debt risks.

Enterprise Debt Risk Management

Suppose we consider a company that needs to manage the risks in its debt portfolio. Traditional risk management methods may include methods based on financial ratios and credit ratings, but these methods may not fully consider the uncertainty and complexity of the market. In this case, the QGA-BP neural network can be applied to enterprise debt risk management to provide more accurate and targeted risk assessment and warning mechanisms.

1. **Data collection and preprocessing:** Firstly, enterprises need to collect relevant debt data, including debt amount, repayment term, interest rate, and so on. Then, they must preprocess the data, including steps such as data cleaning, feature selection, and standardization, to ensure the accuracy and consistency of the data.
2. **Model training and optimization:** Next, use the QGA-BP neural network to model and predict debt risk. By using debt information and other relevant indicators as inputs, the QGA-BP model can learn complex nonlinear relationships and predict the probability of debt default. During the training process, the QGA optimization algorithm is used to optimize the weights and biases of the neural network to improve the accuracy and stability of the model.
3. **Risk assessment and warning mechanism:** Based on the trained QGA-BP model, enterprises can conduct risk assessments on new debts and generate corresponding risk warnings. When the model predicts a high probability of default for a certain debt, the enterprise can take corresponding measures, such as adjusting repayment plans and seeking financing, to effectively manage debt risk.
4. **Continuous monitoring and updating:** Debt risk is a dynamic process that requires continuous monitoring and updating of models. Enterprises can regularly collect new debt data and use this data to retrain and optimize the QGA-BP model to ensure its accuracy and adaptability.

Through the above case study, we can see the application of QGA-BP neural network in enterprise debt risk management. It can provide more accurate and targeted risk assessment and warning mechanisms by learning complex nonlinear relationships and using QGA optimization algorithms, helping enterprises effectively manage debt risks.

The QGA-BP model can also be applied to the following problems.

- **Risk management:** Financial risk management is one of the important tasks in the financial field. The QGA-BP model can be used to establish risk prediction models, helping financial institutions and investors evaluate and manage risks. By training historical data, the QGA-BP model can identify potential risk factors and predict potential future risk events. Future research can explore how to further improve the QGA-BP model to improve the accuracy and stability of risk prediction.
- **Optimization of trading strategies:** Optimization of trading strategies in financial markets is a key issue. The QGA-BP model can be used to construct trading strategy models, automatically discovering and optimizing trading strategies by learning historical market data and trading rules. Future research can explore how to combine the QGA-BP model with other technical means, such as reinforcement learning and deep reinforcement learning, to further improve the effectiveness and adaptability of trading strategies.
- **Financial market prediction:** The QGA-BP model can be used to predict financial markets, including stock prices, exchange rates, and commodity prices. By learning and modeling historical market data, the QGA-BP model can provide predictions of future market trends. Future research can explore how to improve the QGA-BP model to handle nonlinear relationships, long-term dependencies, and other characteristics in financial markets and combine it with other data sources such as social media data and news events to improve the accuracy and practicality of predictions.
- **Financial fraud detection:** Financial fraud is a serious problem that affects financial security and stability. The QGA-BP model can be used to construct fraud detection models, automatically detecting potential fraudulent behavior by learning normal and abnormal transaction patterns. Future research can explore how to further improve the QGA-BP model to improve the accuracy and real-time performance of fraud detection and combine other technical means such as graph networks and anomaly detection to enhance the performance and robustness of fraud detection systems.

In summary, in future financial research, the QGA-BP model can be widely applied in risk management, transaction strategy optimization, financial market prediction, and financial fraud detection. Further research can focus on improving the performance and adaptability of the model, as well as improving the accuracy and effectiveness of financial decision-making.

Analysis of the Limitations and Coping Strategies of the Application of the QGA-BP Model

In the field of finance, artificial intelligence technology has been widely applied, among which the QGA-BP model, as a hybrid model based on quantum genetic algorithm and BP neural network, is increasingly used in financial forecasting, transaction strategy optimization, and risk management. However, with the continuous changes and increasing complexity of financial markets, the QGA-BP model also faces some limitations and challenges. Therefore, future research needs to further explore how to improve the QGA-BP model, enhance its adaptability and performance, to cope with the increasingly complex and changing financial market environment.

- **Nonlinear relationship modeling:** Financial markets and economic systems typically have complex nonlinear relationships, which traditional linear models may not be able to capture. The QGA-BP model, as a hybrid genetic algorithm and BP neural network model, can to some extent handle nonlinear problems. However, for extreme nonlinear relationships, the QGA-BP model may still have insufficient modeling capabilities. To address this challenge, it is possible to consider introducing more complex network structures, such as deep neural networks, to enhance the nonlinear fitting ability of the model.

- **Data quality and noise:** Financial data often contains noise and outliers, which may have a negative impact on model training and prediction results. The QGA-BP model is sensitive to data quality and distribution, and noisy data may lead to a decrease in model performance. To address this issue, data cleaning and preprocessing techniques such as outlier detection, noise filtering, and smoothing can be adopted to improve the quality and accuracy of the data.
- **Long term dependency modeling:** In the financial field, past data often has a significant impact on future predictions, and the QGA-BP model may have difficulties in handling long-term dependency relationships. This is because traditional BP neural networks are prone to gradient vanishing or exploding during the backpropagation process. To address this challenge, some improved BP algorithms such as the long short-term memory network (LSTM) or the gated recurrent unit (GRU) can be considered to enhance the model's ability to model long-term dependencies.
- **Explanatory and understandable nature:** In the financial field, the explanatory and understandable nature of decisions is crucial for investors and regulatory agencies. However, as a black box model, the results and decision-making process of the QGA-BP model are difficult to explain and understand. In order to improve the interpretability and comprehensibility of the model, techniques such as feature importance analysis and decision path analysis can be used to help explain the decision basis and results of the model.

Overall, the application of the QGA-BP model in the financial environment faces some limitations and challenges. By adopting appropriate response measures, such as introducing more complex network structures, data preprocessing, improved BP algorithms, and interpretive techniques, the performance and reliability of the model can be improved, and its application potential in the financial field can be enhanced.

CONCLUSION

In China, the risk of local government debt has always been a focus of close attention for economic observers both domestically and internationally. Traditional financial models have limitations in dealing with such complex and ever-changing problems, so it is necessary to explore new methods and technologies to better understand and predict local government debt risks. In this context, this study adopts a QGA optimized BP network to provide an innovative method for debt risk assessment on government platforms. The proposal of this method is based on a deep understanding of the problems existing in traditional BP models, including challenges such as iterative redundancy and arbitrary trapping. By introducing the QGA, we have successfully overcome these issues and improved the accuracy and reliability of government platform debt risk assessment. In the future, we will further research and explore the potential application of the QGA-BP model in the field of corporate finance. This study will help expand the application field of the model and provide effective tools for risk assessment and management in a broader financial field. In summary, the research results of this article not only have practical significance in controlling local government debt risks, but also provide new ideas and methods for risk management in the financial field. However, it is worth pointing out that the continuous evolution and changes in the financial field require continuous innovation and improvement of risk assessment methods. Therefore, we strongly encourage sustained research and cooperation to promote further development in this field, ensuring that the financial system can adapt to future challenges and achieve more sustainable achievements.

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DATA AVAILABILITY

The figures used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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