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Research On Auction Value Assessment Of Financial Non-Performing Assets Based On Bp Neural Network

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Abstract

The proportion and quality of financial non-performing assets is a direct reflec-tion of the risk management ability of banks and financial institutions. Research on the auction value of non-performing assets and the construction of a reliable non-performing asset value assessment model can help improve the efficiency of resource allocation. Taking the first-hand data from Alibaba auction website as the data source, the main influencing factors affecting the auction value of non-performing assets are explored. Again on the basis of BP neural network to construct a model of non-performing assets auction value assessment, and fur-ther make empirical analyses for testing, the model has accuracy, enriches the research of financial non-performing assets assessment.

Keywords

Financial Non-Performing Assets; Value Assessment; Neural Network

1. Introduction

The Third Plenary Session of the 20th CPC Central Committee emphasised ‘accelerating the clearing of “zombie enterprises”, promoting innovation in financial service models, and enhancing the precision and stability of financial supply.’ As the scale of non-performing loans of commercial banks continued to expand, and grey rhino-type risks such as real estate enterprises, local financing platforms and small and medium-sized financial institutions were frequent, which triggered a continuous increase in the rate of non-performing assets(Richa, 2024). Financial non-performing assets make auction valuation a complex and challenging task due to their special characteristics, such as information asymmetry, high value fluctuation and appraisal difficulty. Traditional valuation methods often rely on the experience and subjective judgement of appraisers, making it difficult to accurately reflect the true value of non-performing assets. Therefore, how to scientifically and reasonably assess the value of financial non-performing assets has become an important issue that needs to be resolved in the current field of financial non-performing asset disposal.

The continuous development of advanced technologies such as big data and artificial intelligence provides new ideas for the auction valuation of financial non-performing assets, comprehensively and deeply mining the information of non-performing assets, improving the accuracy and efficiency of valuation. Therefore, the purpose of this paper is to use the neural network to conduct exploratory analysis of financial non-performing assets auction value, establish the valuation system of the main influencing factors of the value of non-performing assets. This can provide decision-making references for financial institutions and regulators, and promote the effective management and disposal of financial non-performing assets.

2.Review of Relevant Research Literature

Financial non-performing assets are characterised by illiquidity, high risk and complex composition. In the auction environment, financial institutions in order to quickly clear will choose to sell at a discount. Therefore, the composition of the auction value of financial non-performing assets needs to solve three problems: clarifying the influencing factors of non-performing assets, clarifying the formation principle of the auction value of non-performing assets and accurately assessing the auction value of non-performing assets.

2.1. Causes of Non-Performing Assets

Non-performing assets (NPAs) are a complex financial issue with multiple causes. From a macro perspective, its main focus is on the government, industry, and institutions. Most scholars believe that government intervention and policy factors lead to non-performing assets. Anand(Anand, 2019) found that internal leadership support, guarantee preference, local government intervention and other factors have a significant impact on the renewal and expansion of non-performing loans. Jordan(Jordan, 2020)suggested that the macroeconomic factors affecting NPLR are GDP growth, public debt, inflation and unemployment. From the micro analysis, E. J.(E. J., 2017) analysed the causes of non-performing assets of commercial banks in depth from the aspects of commercial banks themselves, institutional mechanism, supervision, law and social credit system construction.

2.2. Factors Affecting Non-Performing Assets

The current academic research on the factors affecting the auction value of non-performing assets is mainly summarised in the following three aspects: first, the debt itself. The evaluation of the data of the debt item itself should be carried out, including the total amount of debt, interest on debt, principal on debt and so on. It is the most intuitive quantitative indicators to reflect the size of non-performing assets, reflecting the overall asset quality. If the pledges are easy to dispose of and have a strong realisation ability, then the value of these assets at auction will increase accordingly. Second, the debtor enterprise. Its business condition and enterprise scale directly reflect its solvency, operational efficiency and future development prospects. Third, macro factors. The favourable or unfavourable regional economic situation and the rise or fall of the industry affect the recovery rate of non-performing assets(Sk, 2025). During the economic downturn, enterprises face greater operational pressure, which may lead to more non-performing loans and non-performing assets. Therefore, the auction value of non-performing assets is full of uncertainty.

2.3. Study on The Valuation of Financial Non-Performing Assets

The Financial non-performing assets refer to loans, bonds and other financial products held by financial institutions that cannot be repaid on time and in full because of their low market and recovery values. There are various ways to dispose of financial non-performing assets. But other methods need to coordinate the interests of all parties, are more complicated to operate, require the hiring of professionals to dispose of them, cost more in terms of time and capital. The biggest advantage of auction is that it can make financial non-performing assets be disposed of quickly and efficiently at a reasonable price through marketisation, openness and transparency, and fierce competition. The auction value of non-performing assets is not only a whole process of judgement, past performance as well as future development prospects are important basis, but also involves the market, the assets themselves, laws, policies and other factors of comprehensive consideration.

Regarding the auction value assessment of financial non-performing assets, Thomas(Thomas, 2023)used a panel regression model to predict the recovery probability of bank non-performing assets. Goswami(Goswami, 2022) explored the influencing factors of non-performing assets using Phase II regression analysis. Mani(Mani, 2023) develops a Structural Satellite version of the Financial-Macroeconometric Model of India to examine. Kumar(Kumar, 2024) understand the non-performing assets of Indian banks based on the application of various data mining techniques like Random Forest, Elastic Net Regression and k - NN algorithm.

After combing through the above literature, Various factors make the auction price of financial non-performing assets tend to be lower and more volatile, and at the same time, it also puts forward higher requirements on the risk assessment ability of investors. Traditional methods lack applicability and require a large amount of company information and personnel to work with them, which clearly does not fit the asset auction scenario. Nowadays, more and more artificial intelligence technology is used in asset evaluation, but there are few studies on the auction value of non-performing assets. In view of this, this paper combines the influencing factors of non-performing assets and asset evaluation theories, and innovatively introduces the BP neural network model to empirically analyse the value evaluation of non-performing assets, with the aim of providing financial institutions and regulatory bodies with more convenient and efficient valuation services.

3. Theoretical Analysis of The Valuation of Financial Non-Performing Assets

The history of financial non-performing asset value assessment in China is only more than twenty years, and the theory of assessment methods is still not perfect. Auction as an important way of non-performing assets disposal, the accuracy and reasonableness of its valuation directly affects the fairness and efficiency of the auction market. Then, exploring scientific and reasonable auction valuation methods can reduce the subjectivity and uncertainty in the valuation process and help assets disposal in bulk. The following is an analysis and comparison of the applicability of the main asset valuation methods for financial non-performing asset values.

Hypothetical liquidation method. It applies to situations where the debtor does not have the ability to continue operations or has a very small or unstable cash flow, and it is theoretically justified and practically feasible to verify the assets and liabilities of the debtor enterprise. However, the accuracy of the appraisal results depends to a greater extent on the financial information provided by the debtor enterprise, and the appraisal results will be biased if the financial information is falsified or the debtor enterprise does not cooperate.

Transaction case method. The biggest advantage of the transaction case method is that it is simple, intuitive and easy to understand, and it can quickly and effectively reflect the market value of the target asset when there is sufficient market transaction data. However, China's non-performing assets trading market is not active enough and the information is not open enough and the auction value of non-performing assets is complicated, so it is difficult to select comparable cases.

Cash flow debt service method. Cash flow debt service method is applicable to the debtor has the ability to continue operations and can produce stable cash flow of the enterprise, cash flow, debt service life, the determination of the discount rate are with a certain degree of subjectivity, the discount rate and the calibre of the cash flow requirements of unity. Most of the auction enterprises are on the verge of closure, without stable cash flow. Therefore, the cash flow debt service method is not an ideal method for the appraisal of non-performing assets.

BP neural network method. In recent years, BP neural network has been widely used in many fields of non-performing asset value assessment, such as stock price prediction, second-hand house value assessment and patent value assessment, etc. It is more efficient and accurate than the traditional manual assessment method, especially suitable for complex and large-scale asset assessment.BP neural network model is able to learn and adjust its own parameters in real time to adapt to the market changes. Moreover, the BP neural network algorithm has been able to effectively handle data from different sources. Therefore, this paper chooses BP neural network as a method for the assessment of the value of non-performing assets to construct a scientific and accurate assessment model.

4. Financial Non-Performing Assets Value Assessment Model Based on BP Neural Network

BP neural network is a multi-layer feed forward neural network trained by error back propagation algorithm. It consists of an input layer, a hidden layer and an output layer, and each layer contains a number of neurons. BP neural network can find out the complex non-linear relationship between input and output, learn effective features from the input through training data automatically, and adjust adaptively to changes of the training data to adaptively adjust to deal with complex pattern recognition and classification problems(Junyang, 2024).

4.1. Source of Data

The data samples of this study are selected from Ali Auction website https://zc-item.taobao.com/, from which the real data of transacted non-performing claims from 2015 to 2024 are selected, and the transaction process is open and transparent, which has a referable value. From it, 2749 transaction samples are selected, of which 2729 samples are used as study samples and 20 samples are testing samples.

4.2. Important Features Screening

This paper examines a type of loan that generally has a clear title in rem as a collateral asset, with a credit facility or through a secured party that provides a guarantee method for it. The input indicators are selected to determine the main value influences on the value of financial non-performing assets, and the more significant factors such as debt status, enterprise status, and market conditions are chosen as the drivers of the model.

1) Claim status, including the principal amount of the claim, collateral and security. the amount of the claim and the way of guaranteeing the claim have a direct impact on the recovery rate of non-performing loans. In general, the auction value of non-performing assets decreases gradually with the security method from credit loans to guaranteed loans to mortgages and mortgage-guaranteed loans.

2) The status of the enterprise, including the region in which it is located and the industry to which it belongs, and the enterprise's operating conditions. The enterprise industry will affect the situation of the enterprise available for realisation of assets, the more assets available for realisation, the wider the asset versatility of the enterprise, the asset recovery rate is relatively high. The economic condition of the region in which the enterprise is located will affect the operation of non-performing assets and the number of potential investors.

3) Market conditions. This includes the number of applicants, the starting price and the disposal package. It is generally accepted that the number of participants in a transaction affects the price of the transaction. A low starting price may stimulate more bidders to participate in the bidding, but may also sometimes allow the auctioneer to sell at a lower price than expected.

According to the purpose of this study set the output data as the transaction price of non-performing assets, which is intuitive. The design and quantification of the input and output indicators are shown in **Table 1**.

Table 1. Input-output indicators and quantification methods.

notation	Hidden meaning	breadth
Y	price reached in an auction	Actual disposal price of assets
X1	loan principal	Principal of loans against disposed assets
X2	Type of guarantee	Pure credit, guaranteed loans, mortgages, mortgages or pledges plus guarantees in order of value 1-4
X3	Type of collateral	Machinery and equipment, land, industrial, residential property, office, commercial property land in order 1-6
X4	industry structure	Agriculture, other, commerce, services, industry, real estate in that order 1-6
X5	Regional location	Below the county level, county-level, prefecture-level and provincial capital cities take values 1-4 in that order.
X6	business situation	Insolvency, shutdown, semi-shutdown, policy in order of value 1-4
X7	Number of applicants	Based on actual number of participants enrolled
X8	starting price	Minimum starting price set by the auctioneer
X9	Mode of disposal	Whether to pack or not, take 1 for non-packing, take 2 for packing.

4.3. Learning and Training of BP Neural Network Models

First create the newcf function of the neural network, the format of the newcf function selected for this article is:

Net=newcf(P,T,[S1,S2...S(N-1)],{TF1,TF2...TFN},BTF,BLF,PF,IPF,OPF,DDF)

This time, we choose 9 influencing factors of auction value of non-performing assets, so the number of neurons in the input layer of the BP network is set to 9. According to the empirical formula for the selection of the number of neurons in the hidden layer, l=root (n+m)+a, where,n is the number of neurons in the input layer, m is the number of neurons in the output layer, and a is a constant between [1,10]. This time, the number of neurons in the hidden layer is set to 10 and the output indicator is 1.

In this paper, we choose the gradient descent method to learn the training of samples. That is, according to the direction of each negative gradient to determine the direction of iteration, and provided to the gradual iteration after making the model to reduce the number of objective functions to be optimised. A simple form of gradient descent method is as follows:

$x(k+1)=x(k)-a\times g(k)$

where a is called the learning rate and g(k) is the gradient of x(k).

In this study, according to the number of sample data, as well as the operation of the programme, the frequency of round display in gradient descent is set to 1000, the learning rate is 0.015, the maximum training rounds is 10000, and the mean square deviation is 0.00065.After setting the training parameters, the train function is called to train the BP neural network. 2729 sample data were used to construct the BP neural network simulation model.

The following fit was obtained by running the programme through MATLAB (see **Figure 1**).

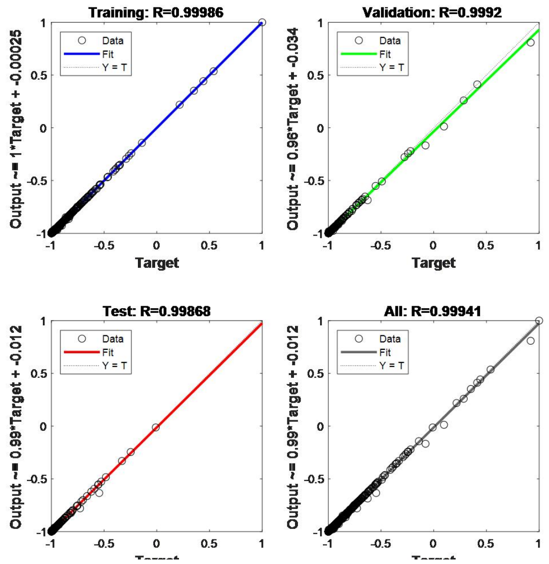

Figure 1. BP regression diagram.

As can be seen from the trend of the two discounts in the above figure, the output values of the 2729 samples are basically in agreement with the fitted values, and the R-value of the model is 0.99 or more, which is generally considered to be a satisfactory fit for the model.

4.4. Simulation Prediction and Testing of Bp Models

The simulation process of a neural network is essentially a process in which the neural network uses the input data as a learning material and derives the corresponding network output by calculating the values according to a set algorithm. In this paper, sim function is used to simulate the trained network. an=sim(net,pn); (3.5) a=postmnmx(an,mint,maxt); Where sim(net,pn) means to simulate with the trained model; postmnmx(an,mint,maxt) means to reduce the data obtained from the simulation to the original order of magnitude.

In order to test the simulation effect of the model, 20 samples were used as test samples and the following simulation output values were obtained (see **Figure 2**)

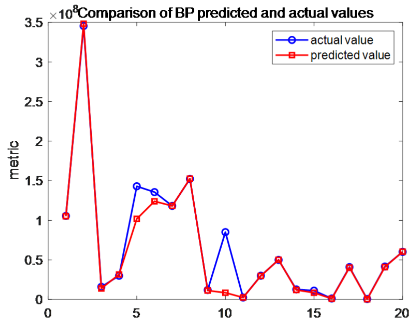

Figure 2. Plot of BP predicted vs. actual values.

The comparison shows that the simulation output values are relatively close to each other, which indicates that the simulation effect of the model is relatively ideal, and it can be applied to the next case study to verify the application value and reference value of BP neural network in the actual business processing through actual cases.

4.5. An Example of The Application of Bp Neural Network Model in Auction Value Assessment of Distressed Assets

This part demonstrates the steps of applying the BP neural network model in the assessment of the recovery rate of non-performing claims with a real case study.

As an example of distressed claims actually transacted in Taobao auctions, a randomly selected case of a debt transaction by Industrial Bank Co.'s Ningde branch on the claim of Fujian Hongxin Machinery Co.

The first step, the collection of non-performing claims related information is as follows: the starting price of 1,000,000, not packaged for processing, the principal amount of the claim 12999955.27 yuan, the outstanding interest 2104375.59 yuan, the total amount of principal and interest 15104330.86 yuan, according to the interest rate of the loan is 4.9%, the calculation of the loan term of 3.3 years, the security mode for the collateral plus the guarantee, the collateral for the fujian hongxin Ltd. is located in Fuan City, Saiqi Development Zone Industrial Park, Daliubian 1, 2 industrial real estate, the creditor is the first claimant, the collateral has been seized, is currently in the implementation. Debtor business industry for the manufacturing industry, the region of Fuan City, Saiqi Development Zone Industrial Park, the auction for the first auction, set the intention of the investor for three people.

In the second step, the above information is quantified according to the rules, with a claim security method of 4, collateral type of 3, region in which it is located of 2, industry type of 5, business status of 4, and set enrolment number of 3, which results in the non-performing claim vector of [12999955.27,4,3,5,2,4,3,1,000,000,1].

The third step is to put this input data into the test set and run the code, which can get the result in the test_simu file.

According to the model prediction result, the auction price of this debt should be 11.69 million yuan, after the network inquiry the final actual transaction price of this debt is 10.98 million yuan, the actual transaction price is 710,000 yuan different from the model prediction, the difference rate is 6%, which shows that the model prediction and the actual transaction results, as shown in **Figure 3**.

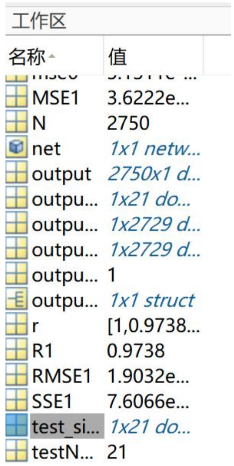

Figure 3. Predicted effect diagram

According to the results of the model prediction, the auction price of the debt should be 11.69 million yuan, after the network inquiry the actual transaction price of the debt was 11.25 million yuan, the difference between the actual transaction price and the model prediction was 440,000 yuan, a difference rate of 3.6%, indicating that the model prediction and the actual trading results

5. Conclusion and Analysis

With the help of big data and computer intelligence learning, it is possible to establish the auction value model of non-performing assets based on BP neural network, which, on the one hand, does not require appraisers to master a more complex theoretical foundation, and on the other hand, can solve the problems of strong subjectivity of the existing appraisal methods in the assessment of non-performing debts and high data requirements of the debtor enterprises.

Since the accuracy of neural networks is based on the amount of learning and the way of learning, it is necessary to repeatedly test the effects of various learning methods on the appraisal results in appraisal practice in order to confirm the relatively effective learning model. In this study, the neural network-based appraisal model for distressed claims is examined and tested by collecting and aggregating some of the publicly available distressed claims transaction data on the Internet, and is used for the prediction of the auction value of distressed assets. The learning and prediction of the study is based on MATLAB, and the application of the model requires that the evaluator masters the basic operation of MATLAB. The complexity of financial non-performing assets makes the requirements of financial non-performing assets appraisal relatively higher and stricter, and at this stage, the appraisal industry still has much room for improvement in the education, seminar and training of financial non-performing assets appraisal. This aspect also limits the promotion and use of the model, which needs further research.

References

[1] Richa Verma Bajaj, Gargi Sanati & (2024). Impact Assessment Study of NPAs and Rate of Recovery: Are Private Sector Banks in India Better off?. Global Business Review, 25(3), 724-749.

[2] Anand Kumar Mishra, Manish Kumar Pathak & (2019). Theme: The hazards of impulsive growth in Non-Performing assets title: A descriptive analysis of the severity, causes and cures to the problem of Non-Performing assets in Indian Banking Industry. ZENITH International Journal of Multidisciplinary Research, 9(3), 331-342.

[3] Jordan Kjosevski & (2020). Macroeconomic and bank-specific determinants of non-performing loans: the case of baltic states. Empirica, 48(4), 1-20.

[4] E. J. Helge & (2017). Empirical Analysis of Non-Performing Assets of Buldhana Urban Co-Operative Credit Society. Journal of Commerce and Management Thought, 8(4), 790-801.

[5] Sk Mujibar Rahaman & (2025). Identifying Key Drivers of Non-Performing Assets in Indian Public Sector Banks: A Panel Data Analysis. IIM Kozhikode Society & Management Review, 14(1), 7-23.

[6] Thomas, R. , & D'Oca, G. . (2023). Modelling the effectiveness of the loan recovery strategy of indian banks. SN Business & Economics.

[7] Goswami, A. . (2022). Covid-19: boon/disguise for indian banks?. Journal of Banking Regulation.

[8] Mani Nithin, Mishra Alok Kumar, Pandikasala Jijin, et al. How Serious is India’s Non-performing Assets Crisis? A Structural Satellite Version of the Financial-Macroeconometric Model[J]. Asia-Pacific Financial Markets, 2023, 30(4):761-794.

[9] Kumar Gaurav & (2024). Data Mining Techniques for Predicting the Non-performing Assets (NPA) of Banks in India. 133-150.

[10] Junyang Wang, Limin Zhang, Xiang Liu, Jinchan Zhang, Wanxin Wang & (2024). Prediction of Mechanical Properties of Cotton Fibers by a BP Neural Network Model Optimized by Genetic Algorithm. Journal of Natural Fibers, 21(1),