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Research on the Construction of Intelligent System for Risk Management and Decision Making in Green Financial Markets

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Abstract: - The evolution process of green financial risk includes three links: risk shock, contagion and diffusion. This paper constructs a green financial development level indicator system to evaluate the development effectiveness of green finance. Through intelligent engine design, artificial intelligence modeling, automatic identification of suspicious risks, dynamic one-click reporting, etc., the design decision-making intelligent system combines principal component analysis and BP neural network algorithm to establish a BPNN green financial risk early warning model, learn and train historical financial data information, and warn of risks in the green financial market, accurately capturing the changes in green financial market risks. The results show that the BPNN green financial risk early warning model established in this paper has a high accuracy rate at all warning moments, with an average accuracy of 0.9952 and a shortest decision time of 530ms. The system in this paper performs very well in short-term prediction, which helps to promote the advancement and development of the green financial system.

Keywords: green financial risk; indicator system; artificial intelligence modeling; decision intelligence; BP neural network

1. Introduction

Green finance, as a policy tool to guide social and economic resources through asset pricing and value circulation to promote sustainable development, is particularly important in the current critical period of economic restructuring and transformation of development mode [1-2]. The traditional economic development model at the cost of environmental damage is in urgent need of reform, and green finance can not only improve capital gains by optimizing resource allocation, but also strongly support the development of green environmental protection industry, which is a key means to enhance the quality of economic development [3]. With the continuous deepening of financial globalization and liberalization, the links between the financial markets of various countries have become increasingly close, and the vulnerability of the financial system has also risen, and the global financial crisis has brought serious impacts to many countries. Since then, maintaining financial stability has become a core issue that countries focus on at the level of financial strategy. How to timely and effectively monitor and identify the pressure situation of the green financial market, early warning, prevention and resolution of financial risks, in order to maintain the stable development of the green financial market, has increasingly become the focus of scholars' attention at this stage [4-5].

In this context, it is of great practical significance to research on the construction of an intelligent system for risk management and decision-making in green financial market. This paper combines risk impact-risk contagion-risk diffusion, which are the three links of systemic financial risk generation and evolution, and then

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establishes the index system of green financial development level, which covers green credit, investment, securities, forestry output value and other aspects. Secondly, a decision-making intelligent system construction is established, which can effectively deal with multi-source heterogeneous data and provide accurate risk management decision support. Finally, the BPNN green financial risk early warning model is introduced, which improves the convergence speed and global optimization seeking ability by improving the standard BP algorithm, and provides powerful technical support for risk management in green financial market.

2. Related Words

In the research on decision-making in the green finance market, Wu, Y et al. constructed a decision-making objective function based on the characteristics of agricultural orders to ensure the sustainable development of green agriculture, and combined game theory to analyze the decision-making behavior of participants in the agricultural supply chain, so as to improve the level of green financial innovation and improve corporate profits [6]. Ling, X et al. studied the management of green credit policies and investment decisions, taking Chinese listed companies from 2008 to 2020 as the research objects, and found that green credit policies have a more obvious effect on companies with high corporate governance levels. The research results help financial institutions to reasonably allocate green credit [7]. Ge, Y et al. explored the risks of green credit and stock price collapse, which are reflected in companies with low audit quality and high marketization, and are conducive to the green transformation of the energy industry [8]. Wei, J et al. used integer patterns, geometric recognition and other methods to establish a life cycle for testing green energy investment. It is concluded that in the green energy industry, the development of new technologies should adapt to investment models and conduct equity financing according to preferences [9].

Some scholars have also conducted research on risk management in the green finance market. Zhao, H. used the BP neural network model to establish evaluation indicators for risk management of the supply chain in green finance. By using the nonlinear mapping ability and flexible network structure of the BP neural network, the project risk level was determined and a control strategy was proposed to ensure the orderly progress of green finance business [10]. Taghizadeh-Hesary, F et al. proposed feasible solutions to the green financing gap in order to solve the problems of financing difficulties, low returns and many risks faced by green energy. For example, through the establishment of trust funds, the use of policies to avoid investment risk measures [11]. Yuan, X et al. proposed using quantum correlation to analyze the financial market system. They verified that financial information linkage is integrated and the spillover effects of various variables fluctuate over time. This study can provide a reference for avoiding financial market contagion risks and promoting the sustainable development of the green investment industry [12]. To avoid the risk of supply chain disruption in green finance, Cheng, J et al. found in their analysis that it is necessary to determine the threshold of input level in the green financial system and then select the financing model [13].

3. Green finance market risk analysis

3.1 Evolutionary process of financial risk and risk management

Green finance risks are summarized as external shocks from the real economy or internal shocks within the financial sector, amplified by contagion from excessive linkages between financial institutions within the financial sector and between green finance markets, leading to increased losses for the financial sector as a whole [14-15]. At the same time, the overall weakening of the financial sector's function will further spread the risk to the real economy, resulting in more serious negative externalities. On this basis, this paper, in order to facilitate the understanding of the evolution process of green financial risk is split into the three links of risk impact, risk contagion and risk diffusion, and Figure 1 shows the evolution path of green financial risk.

The evolutionary process of green financial risk is disassembled into three stages of risk impact, risk contagion and risk expansion, which stands more in the perspective of the downward green financial cycle of risk realization, and is more conducive to the comprehensive and in-depth analysis of the risk-generating mechanism of each evolutionary link, and grasping the essence, grasping the key points and finding the causes through the complex phenomenon [16-17]. However, in the process of green financial market risk management, it is often necessary to pay more forward-looking attention to the accumulation of risks in the process of upward financial cycle [18]. Therefore, from the perspective of the cause and effect of green financial risk generation, the cause of green financial risk generation corresponds to the accumulation of risk shocks in the first link, and the correlation mechanism in the second link of risk contagion. The effect of green financial risk generation corresponds to the final realization of the second link risk contagion and the negative externality of the third link risk diffusion.

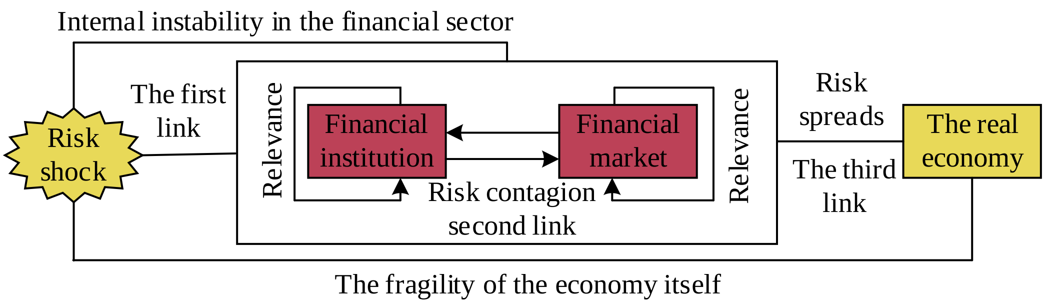

Figure 1 Evolution path of green finance risks

3.2 Construction of Green Finance Development Level Indicator System

In the process of promoting energy efficiency and efficient utilization of resources, the foundation of green finance is to support the green transformation of traditional energy. In order to evaluate the effectiveness of early green cash reforms, this study used green cash risk adjustment as an analytical tool and focused on the second ranked economic value added among nine green finance reform pilot points from 2017 to 2021. A total of 14 secondary indicators, including green credit, green investment, green securities, forestry output value, carbon emission quotas, total energy consumption, and regional GDP, were selected to construct a comprehensive indicator system that reflects the level of green finance development [19-20]. The development of this index not only provides important information for green cash innovation in various regions, but also provides a solid foundation for wise decision-making in green cash business.

Green credit utilizes financial leverage to achieve environmental governance, effectively promoting the transformation of economic development from extensive to intensive. Green investment, also known as social responsibility investment, refers to increasing funds for green GDP in an environmentally friendly manner, which can reflect the relationship between economic and ecological harmonious development. Green securities are economic policies adopted by listed companies in the financing process. The data disclosure system can curb the blind expansion of the three major industries. Forestry, as the core supporting field of green finance, can encourage the construction of green carbon banks and the updating of common forest tenure systems. Carbon dioxide emission quotas are the process of transforming non emitting areas into scarce quotas by limiting the upper limit of corporate carbon dioxide emissions. The total energy consumption is the total amount of energy consumed by the research object in a certain period of time, which is reflected in the degree of constraint of green finance [21]. Traditional industries that consume energy. Regional GDP includes regional GDP and consumer price index, reflecting the impact of green industries on regional GDP during the development of the financial industry.

Table 1 Indicators of green finance development level

Primary indicator	Secondary indicators	Indicator Definition	Indicator direction
Green credit	Green credit scale	Green credit balance in nine green finance reform pilot zones	+
	Interest ratio	Energy consumption interest/industry total interest	-
Investment	Green environmental protection expenditure ratio	The share of fiscal expenditure in green industries	+
	Proportion of investment by polluting enterprises	Anti-pollution investment as a percentage of GDP	+
Green securities	Green Environmental Protection Market Value	Green enterprises account for the share of financial market	+
	Market value share of “three highs” industries	Polluting companies account for market share	-
Forestry output value	Total output value of forestry industry	Total amount of forestry products expressed in monetary terms	+
Total energy consumption	Total consumption of traditional fossil fuels	Nonrenewable resources	-
	Total consumption of new energy	Renewable resources such as nuclear energy, solar energy, and geothermal energy	+

4. Construction of Intelligent System for Green Financial Decision-making

4.1 Decision-making intelligent system design

In order to maximize the effectiveness of risk management in the green financial market, an intelligent analysis and decision-making support framework for the whole scenario of green financial market, business and risk is constructed, and Figure 2 shows the framework of decision-making intelligent system. Based on the software architecture and functional analysis, the core task objectives of software development include intelligent engine design, artificial intelligence modeling, automatic identification of suspicious risks, and dynamic one-click reporting. The key technologies and considerations in this software development process are summarized to help subsequent development users to refer to and improve. System content includes:

(1) Through the customized ETL tool, it supports the reading and writing of multiple types of database modules, including all mainstream relational databases, NoSQL databases and Hadoop databases, to realize the extraction, preprocessing and transformation of multi-source heterogeneous data resources, and then load them into the data processing platform to achieve the correlation and integration of data.

(2) The distributed graph database structure is adopted to ensure the real-time processing capability of multi-source heterogeneous data, and to avoid data over-sensitivity, over-fitting problems and inefficiency in regression and decision-making. By optimizing the graph computing layer and storage layer, it supports massive sample processing and is suitable for the application scenarios of risk management and decision-making in the green financial market.

(3) Most of the traditional data modeling uses business knowledge, but in the face of the application scenarios such as green finance, where data types are complex, sources are diverse, and the degree of visualization is low, it requires the cross-fertilization of a number of technologies, such as data mining, mathematical statistics, and artificial intelligence, in order to accurately target the risk situation [22]. When constructing the upper-layer application model, a modeling development tool based on a scripting language is used to support the reading of information from multiple types of files, multiple databases, and multiple interfaces.

(4) Intelligent middle stage provides data analysis and information flow interaction and management decision-making services for green financial transaction scenarios, and provides diversified business data support for the upper-layer applications from eight directions: sensing, understanding, statistics, decision-making, displaying, creating, digging, and summarizing, to ensure a more accurate and smarter synergy among the modules.

(5) Based on the understanding of banking data, the visualization module is based on human-computer intelligence, visualizing massive financial account and scene data, and enhancing the quantitative and qualitative analyzability of information.

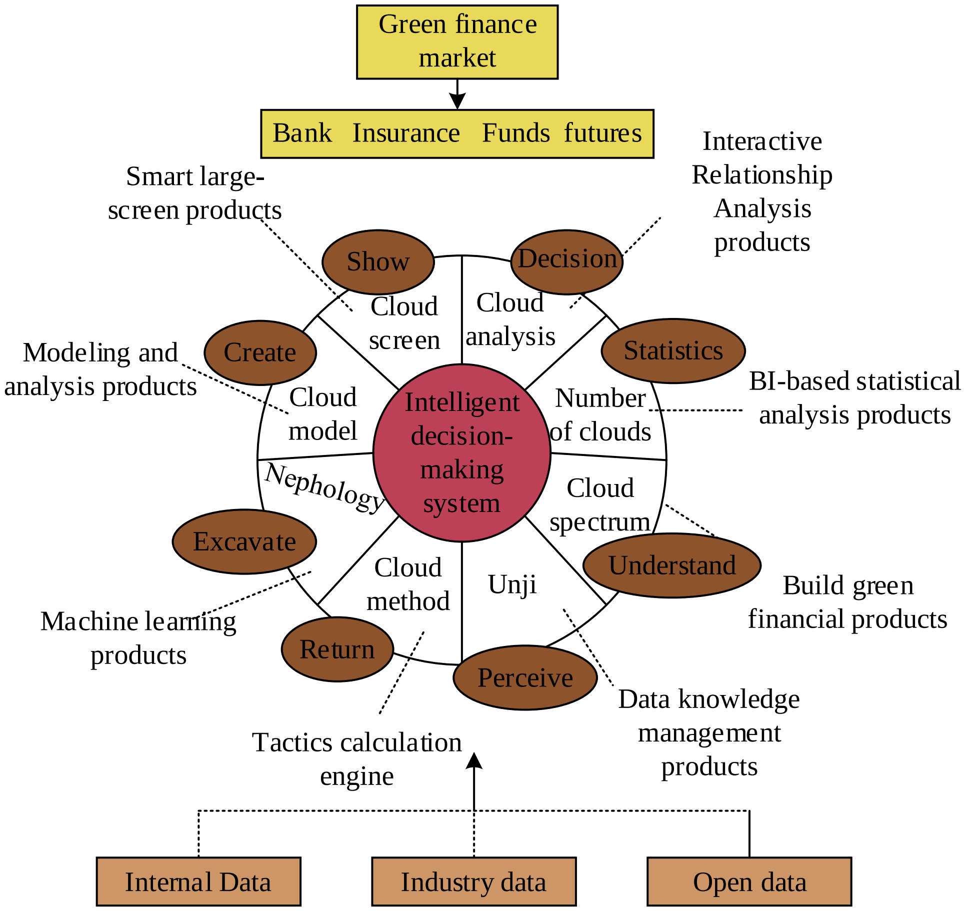

Figure 2 Decision-making intelligent system framework

4.2 Green finance risk early warning model

The BPNN green finance model is a multi-layer feedforward neural network model learned through error backpropagation algorithm[23-24]. It consists of forward propagation of data flow and backward propagation of error signals. The topology diagram of the BPNN model is shown in Figure 3. The state of neurons in each layer only affects the neurons in other layers, and when the output process does not achieve the expected result, the process of error signal backpropagation occurs. Perform gradient descent of errors in the weight vector space through alternating transformations. By dynamically iteratively searching for weight vector sets, the network error function is lower, thus achieving the extraction and training of green finance market data.

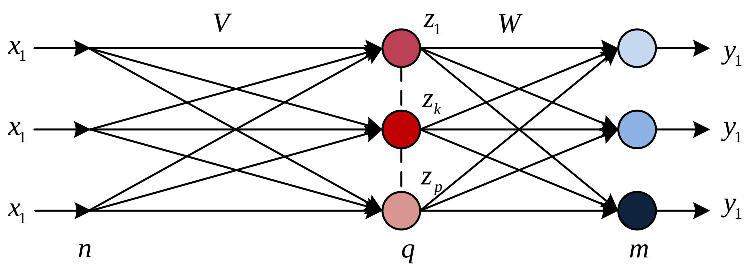

Figure 3 Topological structure of BPNN model

In the input layer, there are n nodes q nodes in hidden layers, input layer m and hidden layers q there are nodes in the, and the weight matrix between the hidden layer and the output layer is v_{ki}, the activation function for the hidden layer is $f_1(\cdot)$, the activation function of the output layer is $f_2(\cdot)$. The output formula for hidden layer nodes is as follows:

$$z_k = f_1\left(\sum_{i=1}^{n} v_{ki} x_i\right)(k = 1,2,3,\cdots,q) \tag{1}$$

The node output of the output layer is:

$$y_j = f_2\left(\sum_{k=0}^{q} w_{jk} z_k\right)(j = 1,2,3,\cdots,m) \tag{2}$$

In a BP neural network, when the output result does not match the expected output result, the error information is back-propagated and the error is reduced by adjusting the weights and bias values in the network. Assuming that the input of p training sample, denoted by $x_1, x_2, \cdots, x_p$, and the p rd sample is input to the network to get an output of $y_j^p\left(j = 1,2,3,\cdots,m\right)$, the error conduction function is set as a squared error function, i.e., the error of the p th sample E_p can be expressed as:

$$E_p = \frac{1}{2}\sum_{j=1}^{m}\left(t_j^p - y_j^p\right)^2 \tag{3}$$

where t_j^p is the desired output and the full error for all p samples is denoted:

$$E = \frac{1}{2}\sum_{p=1}^{p}\sum_{j=1}^{m}\left(t_j^p - y_j^p\right) \tag{4}$$

In the process of error reverse correction, according to the principle of minimizing all errors, the cumulative error BP algorithm is used to update the weight change. The calculation formula is:

$$\Delta w_{jk} = -\eta\frac{\partial E}{\partial w_{jk}} = -\eta\frac{\partial}{\partial w_{jk}}\left(\sum_{p=1}^{p} E_p\right) \tag{5}$$

where η denotes the training learning rate of the model and defines the error signal as μ_{yj} with the expression:

$$\mu_{yj} = -\frac{\partial E_p}{\partial S_j} = -\frac{\partial E_p}{\partial y_j}\cdot\frac{\partial y_j}{\partial S_j} = \sum_{j=1}^{m}\left(t_j^p - y_j^p\right)f_2^{'}\left(S_j\right) \tag{6}$$

where $S_j = W_j X$ denotes the net input of information to the input layer node j, which is obtained by the chain theorem:

$$\frac{\partial E_p}{\partial w_{jk}} = \frac{\partial E_p}{\partial S_j} \cdot \frac{\partial S_j}{\partial w_{jk}} = \mu_{yj} z_k = -\sum_{j=1}^{m} \left(t_j^p - y_j^p\right) f_2^{'}\left(S_j\right) \cdot z_k \tag{7}$$

Therefore, the weight adjustment formula for each neuron in the output layer is:

$$\Delta w_{jk} = \sum_{p=1}^{p} \sum_{j=1}^{m} \eta \left(t_j^p - y_j^p\right) f_2^{'}\left(S_j\right) \cdot z_k \tag{8}$$

Similarly, the weight change adjustment formula for the hidden layer can be obtained:

$$\Delta v_{ki} = \sum_{p=1}^{p} \sum_{j=1}^{m} \eta \left(t_j^p - y_j^p\right) f_2^{'}\left(S_j\right) w_{jk} f_1^{'}\left(S_k\right) \cdot x_i \tag{9}$$

where $S_k = V_j Z$, denotes the net information input of the hidden layer node k. Although the BPNN model has the advantages of reliable basis and high accuracy, the standard BP algorithm has the problems of slow convergence and easy to fall into local minima. Therefore, the standard BPNN model can be improved by using the additional momentum optimization method. This is done by adding a part of the last weight adjustment amount. That is, the additional momentum is iterated to the weight adjustment quantity obtained by the current error calculation. As the actual weight adjustment quantity for this network learning training, it is expressed by Eq:

$$\Delta W_n = -\eta \nabla E_n + \alpha \Delta W_{n-1} \tag{10}$$

where α is the momentum factor, η denotes the learning rate, and the additional momentum factor is equivalent to the damping term, which mainly serves to reduce the oscillatory tendency during the learning process.

The BPNN green financial risk warning model has the function of comprehensively measuring market risks and can comprehensively reflect the status of financial institutions in assuming market risks and credit risks. It is not only conducive to the identification and control of internal risks of financial institutions, but also provides a market standard for comparing risk levels between financial institutions, which is helpful for the unified supervision of regulatory authorities.

5. Validation of intelligent systems for risk management and decision-making

5.1 Model Training and Evaluation

According to the data of seven green financial indicators in the level of green financial development above, the experiment is conducted, using 8 groups as training samples, and taking 1 group as a test sample for calculation. According to the comprehensive score of green finance evaluation of each region as the output target of the neural network, and then through the MATLAB7.0 for training, the training error changes are shown in Figure 4. The training target is set near 2000, while the training output gradually decreases with time from 3000 to a value close to the training target. This indicates that the model gradually learns and adjusts its parameters during the training process, bringing the output closer to the preset target value. The validation output is around 2500, which is slightly higher than the training target. This is due to the model overfitting on the training set, resulting in less performance on the validation set than on the training set.

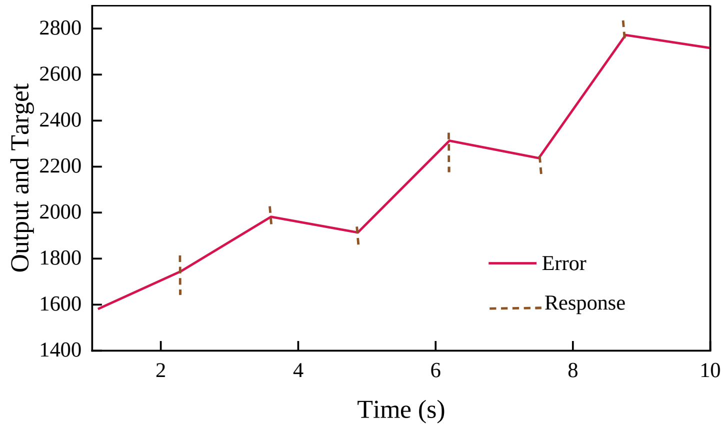

Figure 4 Training error change curve

Based on the established AM-BPNN green financial risk early warning model, network learning and training are performed using historical data and information. The model has high accuracy in risk evaluation. Therefore, this paper specifically analyzes the green finance development status from multi-level areas such as time, geography, market capacity, policy system, and market disclosure. The input and error correlations are shown in Figure 5, and the zero correlation is located at 0.25×10^5 and -0.25×10^5, and the correlation between the instantaneous values of the input nodes and the output nodes within a single moment is high. This can reflect that the BPNN green financial risk early warning model established in this paper can effectively identify risks and make intelligent decisions.

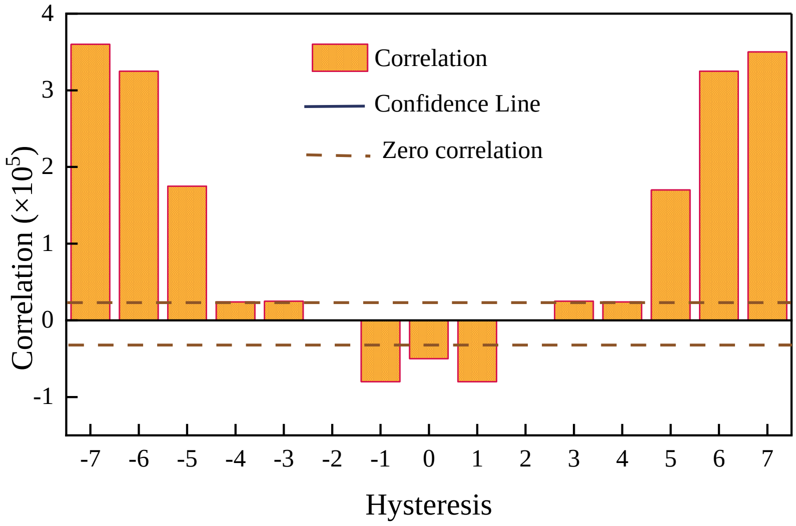

Figure 5 Input and error correlation

The error index is the key to measuring model performance. It reflects the convergence of the model during the training process and is very important for evaluating model performance and optimizing model parameters. Figure 6 shows the error decline curve. The number of iterations indicates the number of model training times, and the mean square error indicates the difference between the model prediction results and the actual results. During the training process, the mean square error changes with the number of iterations. When the number of iterations is 480, the minimum mean square error of the validation set is 10-5. At this time, the model training effect is the best, and the network training process is stable and convergent.

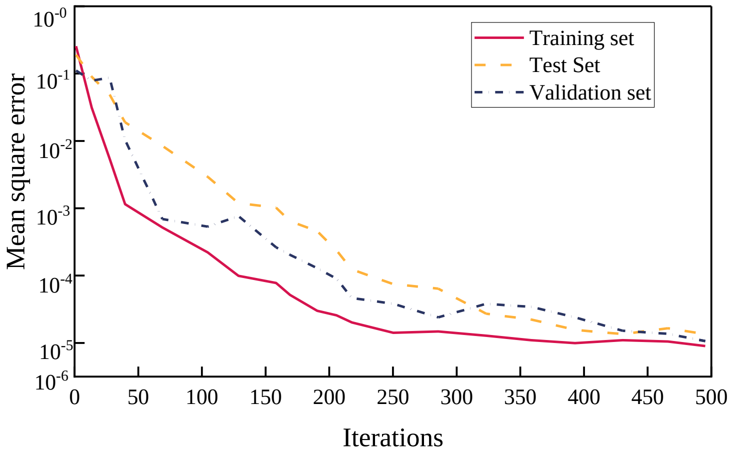

Figure 6 Error reduction curve

5.2 Analysis of financial risk early warning results

5.2.1 Decision time comparison

This paper adds the empirical analysis of ARIMA early warning model and SVM early warning model, and compares their early warning results with the decision time of the BPNN early warning model constructed in this paper. Figure 7 shows the decision time comparison results, in the green financial data volume of 2.0, this paper's AM-BPNN model decision time is 380ms, while the ARIMA early warning model's decision time is 490ms, and the SVM early warning model's decision time is 510ms. With the increase of the data volume of the decision time increases, when the green financial data volume reaches 3.0, the decision time of this paper's BPNN model is the shortest 530ms. The shortest decision time is 530ms, which is due to the algorithm optimization of this model, which can respond quickly and generate decision results.The decision time of ARIMA early warning model is 780ms, which is based on the statistical analysis method of historical data, and needs to consider more historical data points when making predictions and decisions, which leads to a relatively long decision time.The decision time of SVM early warning model is 920ms, which needs to make more decisions when making decisions. Which requires more complex calculations when making decisions, which leads to its relatively long decision time. In contrast, the BPNN model studied in this paper shows significant advantages under green financial market risk management. Its ability to respond quickly and make efficient decisions makes the model more widely applicable in practical applications and able to meet real-time trading decisions in financial markets.

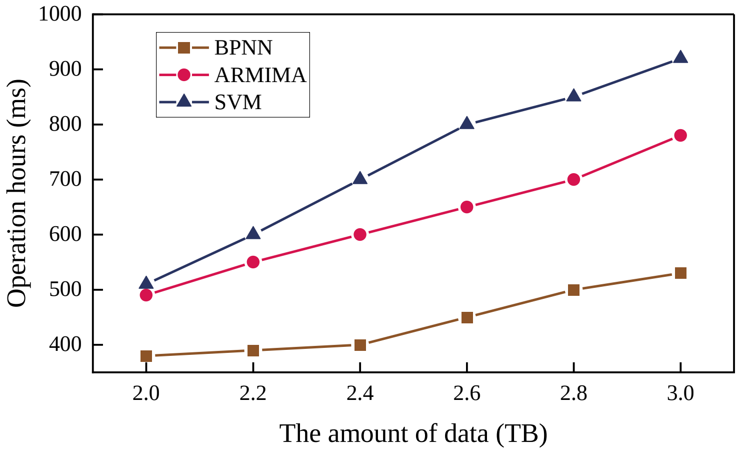

Figure 7 Decision time comparison results

5.2.2 Comparison of average accuracy

In addition, to test the superiority of the BPNN green financial risk early warning model, this paper adds the empirical analysis of the ARIMA early warning model and the SVM early warning model, and compares their early warning results with the results of the BPNN early warning model constructed in this paper, and adds the average accuracy to better compare the performance of the three models in different early warning intervals. The model early warning results are shown in Table 2. The BPNN model proposed in this paper has high accuracy in all early warning intervals, with an average accuracy of 0.9952. Especially in the shorter early warning interval of 2023.06-2024.06, its accuracy reached 1.0000, showing the strong ability of the model in short-term forecasting. The average accuracy of the ARIMA model is 0.9716, which is slightly lower than that of the AM-BPNN model. Although the model performs well in the longer early warning interval, its accuracy decreases in the shorter early warning interval, such as 2023.06-2024.06. The average accuracy of the SVM model is 0.9663, which is the lowest among the three models. However, it is worth noting that in the warning period of 2021.06-2023.06, the accuracy of the SVM model exceeds that of the AM-BPNN model and the ARIMA model, showing its potential advantages in certain specific situations. It is believed that the AM-BPNN model performs best in terms of green financial risk prediction accuracy, especially in short-term predictions.

Table 2 Warning results of different warning models

Warning range	AM-BPNN Model	ARIMA Model	SVM Model
2019.06-2023.06	0.9964	0.9817	0.9693
2020.06-2023.06	0.9953	0.9762	0.9665
2021.06-2023.06	0.9937	0.9745	0.9808
2022.06-2023.06	0.9905	0.9622	0.9714
2023.06-2024.06	1.0000	0.9632	0.9437
Average Precision	0.9952	0.9716	0.9663

6. Conclusion

In this paper, the risk evolution process of green financial market is studied in depth, the corresponding index system of green financial development level is constructed, and the three key evolution links of green financial risk are revealed. In addition, an intelligent decision-making system is proposed to improve the efficiency and accuracy of risk management through functions such as intelligent engine and artificial intelligence modeling. The BPNN green financial risk early warning model was constructed to achieve the goal of accurate early warning of risks in the green financial market. In this study, seven green financial indicators were analyzed in-depth data, and when the number of model iterations was 480, the mean square error of the validation set was minimized to 10^{-5}, and the training effect was most significant. Along with the increasing amount of green finance data, the decision time of this paper's BPNN model is the shortest 530ms compared with other models.In addition, the BPNN model proposed in this paper performs well in risk prediction, with an average accuracy of 0.9952.In short-term prediction, its accuracy is even as high as 1.0000, and it outperforms ARIMA model and SVM model. This proves that the research results of this paper have important reference significance for the innovative development of green finance.

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