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Computer-Aided Design and Applications

Optimization Algorithm for Enterprise Decision Making Based on Big Data Fusion

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Abstract. The rise of big data technology has opened up new horizons for optimizing enterprise decision-making. It can not only process traditional structured data but also deeply explore valuable information in semi-structured and unstructured data. In this era, this article is committed to building an enterprise decision optimization algorithm that integrates computer-aided and big-data technology. We will apply the constructed decision optimization algorithm to the financial risk prediction model and verify its superiority in financial risk prediction through empirical research. The accuracy of this method is 20.01% higher than that of the Support Vector Machine (SVM) algorithm, and the error is reduced by 42.77%. In terms of model stability, backpropagation neural networks (BPNN) have significantly higher stability than other methods. This means that the model constructed in this article can operate more stably in practical applications, providing more reliable support for financial risk management. In the future, we will further explore and study how to apply this model to a wider range of financial scenarios.

Keywords: Computer Assisted; Big Data; Enterprise Decision-Making; BP Neural Network
DOI: https://doi.org/10.14733/cadaps.2024.S21.208-225

1 INTRODUCTION

As science and technology continue to advance at an unprecedented rate, the integration of Computer-Aided Systems (CAS) with Big Data technology has emerged as a pivotal catalyst for optimizing enterprise decisions. In the present interconnected global economy, enterprises are confronted with an ever-evolving and complex business terrain alongside expanded market prospects. With the rise of renewable energy, the wind power industry is rapidly developing globally. Wind power enterprises face fierce market competition and uncertain environmental factors; therefore, it is crucial to develop the optimal bidding strategy and strengthen enterprise risk management. AlAshery et al. [1] explored how wind power companies can combine second-order stochastic advantage constraints to develop bidding strategies to achieve a balance between risk and return. The bidding strategy of wind power enterprises mainly involves decision-making on project scale, technical solutions, cost budgeting, construction period, and other aspects. When formulating bidding strategies, enterprises need to consider their core competitiveness, such as wind turbine manufacturing technology, project experience, financing capabilities, etc. At the same time, it is necessary to analyze competitors and understand market conditions in order to develop the most competitive quotation. Second-order stochastic advantage constraint is a mathematical tool used to describe the advantages of one solution over another in uncertain environments. In wind power enterprises, this constraint can help companies find a balance between risk and return. For example, companies can evaluate the risks and potential benefits of different bidding schemes based on second-order stochastic advantage constraints, in order to select the optimal solution.

Consequently, the adept integration of computer-aided systems with big data technology to enhance the precision and responsiveness of corporate decision-making has escalated into a pressing challenge for contemporary businesses. With the gradual opening of the electricity market and the popularization of renewable energy, distribution companies are facing more and more challenges. Among them, the interaction with the wholesale market and microgrids has become a key issue. In order to better address these challenges, Bahramara et al. [2] proposed a risk decision-making framework based on a BP neural network. Distribution companies play an important role in the electricity market and require effective interaction with the wholesale day-ahead markets and microgrids. However, there are various risks involved in this interactive process, such as price fluctuations, supply-demand imbalance, etc. To reduce these risks, distribution companies need an effective decision-making framework to guide their operations. The risk decision-making framework based on the BP neural network can simulate and predict market behaviour, providing a scientific decision-making basis for distribution companies. In recent years, many scholars have studied the interaction between distribution companies, wholesale day-ahead markets, and microgrids. However, existing research mostly focuses on market pricing and energy scheduling and lacks in-depth exploration of risk decision-making. Although some studies have used neural network methods for risk prediction, they often only consider a single factor and fail to reflect the interaction between the market and microgrids fully. CAS, with its powerful data processing and information analysis capabilities, has become a right-hand man for enterprise decision-making. It can quickly collect massive data inside and outside the enterprise, sort it out and analyze it, thus helping the enterprise to capture the market dynamics and industry context keenly. With the development of globalization and digitization, enterprises are facing increasingly complex and dynamic supply chain environments. Supply chain resilience has become a key capability for enterprises to cope with uncertainty and risks. The rapid development of artificial intelligence (AI) technology provides new opportunities and tools for improving the resilience of enterprise supply chains. Belhadi et al. [3] explored how to use artificial intelligence technology to build enterprise supply chain resilience and introduced relevant technologies and decision-making frameworks. Taking a clothing company as an example, the company utilizes AI technology for demand forecasting and inventory management. By collecting and analyzing diverse data such as sales data, weather forecasts, and fashion trends, AI models can predict market demand for a period of time in the future. Based on the predicted results, enterprises can develop more accurate production plans and inventory management strategies to avoid excessive production and inventory backlog. At the same time, AI technology can also monitor inventory status and sales data in real-time, detect abnormal situations in a timely manner, and take corresponding adjustment measures to ensure the stability of the supply chain and the ability to cope with uncertainty. However, the decision-making method that relies too much on CAS is often too rigid and lacks flexible response and foresight to market changes. With the acceleration of globalization, virtual teams in enterprises have become a common form of organization. However, the decision-making process of virtual teams is influenced by various factors, among which corporate culture intelligence, conflict, and transformational leadership are three important aspects. Davidaviciene and Majzoub [4] explored how these three factors affect the decision-making process of enterprise virtual teams and proposed corresponding suggestions. Corporate culture intelligence refers to the ability of a company to form unique cultures, values, and behavioural norms during its long-term development process. In virtual teams, due to members coming from different regions and cultural backgrounds, corporate cultural intelligence has a significant impact on the decision-making process of the team. On the one hand, if the corporate culture intelligence of a virtual team is high, cultural differences among members will be seen as an advantage, and the team can better understand and adapt to different cultures and market environments, thereby making decisions that are more in line with the actual situation. On the other hand, if a company's cultural intelligence is low, it may lead to communication barriers and cultural conflicts among team members, thereby affecting the quality and efficiency of decision-making.

The rise of big data technology has opened up a new world for enterprise decision optimization. It can not only deal with traditional structured data but also deeply my valuable information in semi-structured and unstructured data. In today's fiercely competitive market environment, setting product prices for enterprises is a key strategic decision. Price not only affects a company's profits but is also closely related to multiple factors such as market demand and competitive situation. In order to better respond to market changes, enterprises need a scientific and effective pricing strategy. Gazijahani and Salehi [5] discussed how to use BP neural networks to handle demand flexibility and provide decision support for enterprise product pricing. BP neural network is a backpropagation neural network that minimizes the error between actual output and expected output by continuously adjusting network weights and thresholds. It has the characteristics of self-learning, self-organization, and strong adaptability, and can handle complex nonlinear problems. In pricing strategies, BP neural networks can be used to predict product demand, thereby helping businesses formulate reasonable prices. Demand flexibility refers to the ability of enterprises to quickly adjust product demands based on market changes. In a rapidly changing market environment, demand flexibility is crucial for the survival and development of enterprises. By improving the accuracy of demand forecasting, enterprises can better cope with market fluctuations, optimize resource allocation, and improve operational efficiency. Through big data technology, enterprises can gain a more comprehensive and in-depth insight into market demand and consumer behaviour, making the decision-making basis more accurate and scientific. With the rapid development of technology, participatory sensing and digital twin technology have brought unprecedented opportunities and challenges to enterprises. Especially in the field of virtual enterprises, these two technologies provide more accurate and real-time data support for risk decision-making. Ham and Kim [6] explored how to use participatory sensing and digital twin technology to update virtual enterprise models to enhance risk-informed decision-making. Participatory sensing technology utilizes various sensors to collect data and conducts real-time processing and analysis through technologies such as cloud computing and big data. In virtual enterprises, participatory sensing technology can be widely applied in fields such as supply chain management and partner monitoring. Through real-time monitoring and early warning, enterprises can better perceive potential risks and provide decision-makers with more accurate risk information. Digital twin technology provides enterprises with a virtual, real-time model that reflects the real world. Through digital twin technology, enterprises can simulate decision-making effects in virtual environments, predict potential risks, and make wiser decisions. In addition, digital twin technology also helps enterprises optimize resource allocation, improve operational efficiency, and further reduce risks. In this era, this article is committed to building an enterprise decision-making optimization algorithm that combines computer-aided and big-data technology. The objective of the algorithm is to enhance the precision of corporate decision-making by leveraging the strengths of both CAS and Big Data technology, thereby equipping businesses to effectively navigate the intricate and fluctuating business landscape. To elaborate, this article initially delves into the current application of CAS and Big Data technology in enterprise decision-making, highlighting their limitations when deployed individually. Subsequently, an innovative decision-making optimization framework is introduced, seamlessly blending the data processing workflow of CAS with the information mining capabilities of Big Data technology, culminating in a novel decision-making optimization algorithm. By constructing this innovative decision-making optimization algorithm, this article aims to provide a brand-new decision-making idea and method for enterprise decision-makers, help enterprises to be invincible in the complex and changeable business environment, and then enhance their overall competitiveness and market position.

With the arrival of the Industry 4.0 era, digital transformation has become an inevitable trend for enterprise development. The digital supply chain twins, as one of the core concepts of Industry 4.0, provide enterprises with a new management model and thinking perspective. Ivanov and Dolgui [7] explored how digital supply chain twins can help businesses cope with management interruption risks, improve resilience, and maintain competitiveness in the Industry 4.0 era. Digital supply chain twins refer to supply chain twins created through digital technology in a virtual environment. This twin can simulate and predict the operation of the real supply chain in real time, providing transparent and visible supply chain management methods for enterprises. The digital supply chain twins can not only monitor the real-time status of the entire supply chain but also predict potential interruption risks through data analysis, thus taking proactive measures. The digital supply chain twins can monitor various links in the supply chain in real time, detect potential interruption risks in a timely manner, and predict the possibility of risk occurrence through data analysis, providing early warning for enterprises. In this algorithm, CAS will give full play to its advantages of data collection and preprocessing and lay a solid data foundation for subsequent information mining. The big data technology will use advanced machine learning and deep learning algorithms to carry out deep mining and knowledge discovery on the preprocessed data, thus providing a more accurate scientific basis for enterprise decision-making. By selecting a representative enterprise case for in-depth analysis, this article will show the outstanding performance of the algorithm in practical application, thus providing a powerful reference for enterprise decision-makers.

(1) This article designs a new decision optimization algorithm, which combines the data processing efficiency of CAS and the information mining ability of big data technology. This algorithm can deal with massive, multi-source, and heterogeneous data and extract valuable information for decision-making.

(2) In this article, the decision-making optimization algorithm is applied to the financial risk prediction model, and the superiority of the algorithm in financial risk prediction is verified through empirical research, which provides a more scientific and systematic risk management tool for enterprises.

In the following chapters, this article will discuss in detail the specific application of CAS and big data in enterprise decision-making, the existing problems, and the necessity and feasibility of their integration. On this basis, this article will put forward the specific algorithm framework and implementation steps and verify and evaluate it through empirical research. Finally, this article will summarize the main findings and contributions of the research and look forward to the future research direction.

2 RELATED WORK

With the rapid development of the food industry, quality credit evaluation of food enterprises has become an important means to ensure food safety and safeguard consumer rights. However, due to the complex and diverse factors affecting food quality, how to accurately and objectively evaluate the quality credit of food enterprises has become an urgent problem to be solved. Jiang et al. [8] introduced a CPT-TODIM method based on image fuzzy multi-attribute group decision-making and applied it to the evaluation of quality credit in food enterprises. Determine the weight vectors of each attribute by analyzing the decision matrix image. Each element of the weight vector represents the relative importance of this attribute in the quality credit evaluation of food enterprises. Calculate the comprehensive evaluation value of each food enterprise based on the weight vector and the attribute values of each food enterprise. Collect relevant data from various food enterprises, including quality inspection reports, production records, customer feedback, etc. Process and analyze these data using the CPT-TODIM method to obtain comprehensive evaluation values for each enterprise. Based on the evaluation results, develop corresponding incentive and constraint mechanisms. For enterprises with high quality and credit, provide policy incentives, market promotion and other support; For enterprises with low quality and credit, strengthen supervision and inspection to urge them to improve their quality. With the advent of the big data era, the risk assessment and control of risk financing for small and medium-sized enterprises are facing unprecedented challenges and opportunities. Big data technology provides more accurate and comprehensive data support for risk assessment, while also placing higher demands on risk control algorithms. Li et al. [9] explored how to use big data technology for risk assessment and risk control of small and medium-sized enterprise risk financing in the context of the big data era. Taking the risk financing of a small and medium-sized enterprise as an example, the enterprise utilizes big data technology to conduct risk assessment and control of risk financing. Firstly, obtain comprehensive and accurate data through big data technology, including the financial status of the enterprise, market trends, etc. Then, use data analysis tools to deeply mine and analyze these data, extracting features related to risk assessment. Next, construct a risk assessment model to predict and evaluate the risks of the enterprise. Based on the evaluation results, set corresponding risk control thresholds and take corresponding risk response measures. Finally, evaluate the effectiveness of the risk response measures taken and adjust and optimize the risk control algorithm based on the evaluation results. Through this approach, the company has successfully reduced the risk of risk financing and improved its robustness and competitiveness. The distributed decision-making model is a networked and intelligent decision-making method that disperses the decision-making process to various organizations or individuals. Through information sharing and collaborative cooperation, it achieves the efficiency and accuracy of decision-making. In virtual enterprises, due to the distribution of organizational members in different regions and organizations, traditional centralized decision-making makes it difficult to meet their rapid response and flexible needs. Therefore, distributed decision models provide an effective solution for risk decision-making control in virtual enterprises. The operation process of virtual enterprises also faces many risks, and how to effectively make risk decision-making and control has become an urgent problem to be solved. Ouyang [10] explored risk decision control for virtual enterprises based on distributed decision models. Taking a virtual automobile manufacturing enterprise as an example, the enterprise has achieved effective control of supply chain risks by establishing a risk decision control system based on a distributed decision model. Firstly, the company has established a supply chain information-sharing platform to collect risk information from various suppliers and share it in real-time. Then, using intelligent risk identification tools, analyze and evaluate this information to determine the supplier's risk level. Next, corresponding response strategies and measures are formulated based on the risk level and optimized and coordinated through a distributed decision-making model. With the rapid development of technology, especially the rapid advancement of computer technology, big data has become an indispensable factor in enterprise decision-making. Effectively integrating computer technology with big data and providing more scientific and efficient support for enterprise decision-making are important issues currently faced by enterprises. Ramamurthy [11] explores a data-driven enterprise decision-making roadmap under the fusion of computer-aided and big data in order to provide useful references for enterprise decision-makers. Computer-assisted technology provides strong support for data-driven decision-making. On the one hand, computers can quickly process massive amounts of data and achieve efficient data analysis. On the other hand, computer technology can help enterprises establish various predictive models, simulate and predict market trends, and provide strong support for enterprise decision-making. In addition, computer technology can also achieve data visualization, making complex data analysis results more intuitive and understandable. Take a certain e-commerce enterprise as an example. The enterprise utilized computer-aided technology combined with big data analysis to construct a data-driven enterprise decision-making roadmap. With the advent of the big data era, enterprises are facing unprecedented opportunities and challenges. Effectively utilizing big data technology to quickly evaluate and manage situational issues in enterprises has become a focus of attention for decision-makers and managers. Shageev and Chuhonceva [12] proposed a universal rapid evaluation and management decision-making method for enterprise situational problems based on big data fusion, aiming to help enterprises better cope with complex and changing market environments. In the era of big data, enterprises are facing massive amounts of data and information, which come from a wide range of sources and diverse types, providing them with abundant information resources. However, there is a significant amount of redundancy, conflict, and uncertainty among these data, which poses certain difficulties for enterprise data analysis and decision-making. Therefore, enterprises need to integrate data from different sources and types to form a comprehensive, accurate, and real-time data view, providing strong support for enterprise decision-making. With the intensification of market competition, selecting suitable distributors has become a key link in enterprise supply chain management. Vats et al. [13] explored a supply chain distributor selection method based on grey decision-making, aiming to provide a new approach and tool for enterprises. Grey decision theory is a decision-making method based on grey system theory, which deals with problems with incomplete information characteristics by establishing models such as grey correlation analysis, grey clustering analysis, and grey prediction. This theory has wide applications in many fields, especially in supply chain management, and can effectively solve complex problems such as distributor selection. Assuming a manufacturing company needs to choose new distributors to expand market share. Firstly, based on the needs of the enterprise and market environment, price, quality, service, delivery time, etc. are selected as evaluation indicators. Then, the grey relational analysis model is used to evaluate the candidate distributors and calculate their correlation with the ideal distributor. Next, conduct a grey clustering analysis to classify distributors with similar correlation degrees for better comparison and selection. Based on the evaluation results and needs, develop corresponding distributor selection strategies. Offshore financial enterprises, as an important component of international finance, have a profound impact on the development of the port economy. With the continuous development of big data technology, it has become possible to conduct in-depth analysis and evaluation of the role between offshore financial enterprises and the port economy. Wang [14] explored how to use big data analysis methods to comprehensively and objectively evaluate the role of offshore financial enterprises in the development of the port economy. The offshore financial enterprise market provides abundant financial support and services for the port economy, effectively promoting the development of the port economy. Firstly, the offshore financial enterprise market can attract a large amount of international capital and provide strong financial support for port infrastructure construction, logistics development, etc. Secondly, the offshore financial enterprise market can reduce the financing costs of enterprises, provide diversified financial services for enterprises, and promote their rapid development. Finally, the development of the offshore financial enterprise market can also drive the development of related industries, such as shipping, logistics, trade, etc., further promoting the diversified development of the port economy. Taking a port in a coastal city as an example, the port has achieved rapid economic growth through the development of the offshore financial enterprise market. Firstly, collect data on the throughput, types of goods, and trade volume of the port in recent years, and obtain transaction data on the offshore financial enterprise market from relevant government departments. Then, using big data analysis methods to process and analyze these data, establish relevant models to predict the development trend of the port in the coming years. With the development of globalization and informatization, risk management in enterprise supply chains has become an important issue. The emergence of blockchain technology provides a new solution for enterprises. By achieving transparency, immutability, and traceability of information, blockchain technology can help enterprises better manage supply chain risks. Zheng et al. [15] explored the application of blockchain in information sharing and how to use blockchain technology for risk decision-making in enterprise supply chains. Blockchain is a distributed database technology that records transactions, contracts, and other information in a decentralized manner and has the characteristics of high transparency, difficulty in tampering with data, and decentralization. Blockchain technology can effectively solve the problem of information asymmetry, improve the security and credibility of information, and provide new ideas for enterprise supply chain risk management. Taking a certain food enterprise as an example, it utilizes blockchain technology to manage its supply chain. By utilizing blockchain technology to achieve transparency and immutability of information, the enterprise is able to monitor the procurement, production, logistics, and other aspects of raw materials in real-time, ensuring the safety and quality of its products.

3 THE APPLICATION OF BIG DATA TECHNOLOGY IN ENTERPRISE DECISION-MAKING

Since its birth, CAS has played an increasingly important role in enterprise decision-making with its powerful data processing and information analysis capabilities. With the progress of technology and the deepening of application, CAS has penetrated into all aspects of enterprise management and has become an important tool to promote the scientific decision-making of enterprises. The core function of CAS is that it can process and analyze a large amount of data quickly and accurately. By using advanced mathematical models, algorithms, and simulation technology, CAS can comprehensively evaluate all kinds of information inside and outside the enterprise, thus providing comprehensive and objective decision support for enterprise decision-makers. In the process of enterprise decision-making, the application of CAS is mainly reflected in the following aspects: Firstly, CAS finds extensive application in market analysis and forecasting. Through the collation and examination of market data, CAS enables enterprises to comprehend market demands and competitive landscapes precisely, laying a crucial foundation for the formulation and adjustment of market strategies. Numerous businesses utilize CAS for market segmentation, identification of target markets, and the development of tailored marketing strategies, thereby elevating their market share and sales performance.

Moreover, CAS occupies a pivotal position in the domains of Enterprise Resource Planning (ERP) and production management. By amalgamating internal resource information, CAS facilitates optimal resource allocation and efficient utilization within enterprises. Additionally, it offers real-time monitoring and analysis of enterprise production processes, enabling prompt identification and resolution of production issues and subsequently enhancing productivity. Furthermore, CAS plays a significant role in enterprise risk management and financial decision-making. Through the establishment of risk assessment models and financial analysis systems, CAS promptly identifies and evaluates a range of potential risks, providing robust support for enterprises in formulating risk mitigation measures and financial decisions.

Although the application of CAS in enterprise decision-making has achieved remarkable results, there are still some problems and challenges. Among them, the most important problem lies in the lack of flexibility and adaptability of CAS. Because CAS is usually designed and developed based on fixed models and algorithms, it is difficult to cope with the complex and changeable business environment and market demand. In addition, there are still some problems in CAS, such as low data quality and hidden danger of information security, which also limit the application effect of CAS in enterprise decision-making to some extent. The essence of big data technology is its capacity to handle and interpret vast, intricate, and multifaceted datasets that surpass the capabilities of conventional data processing methods. These datasets originate from a myriad of sources, encompassing internal business records, external market intelligence, social media platforms, and more. Utilizing cutting-edge algorithms and technologies, such as machine learning and deep learning, big data technology adeptly analyzes this wealth of information to unearth invaluable insights and knowledge concealed within. In the realm of enterprise decision-making, the impact of big data technology is multifaceted:

Primarily, big data technology has become indispensable in predicting market trends and deciphering consumer behaviour. By delving deeply into market and consumer datasets, big data technology empowers enterprises to gain a more nuanced understanding of market fluctuations and consumer preferences. This, in turn, provides a solid foundation for shaping and refining market strategies. For instance, numerous e-commerce ventures harness big data technology to scrutinize user purchase patterns, browsing histories, and other relevant metrics to craft more personalized product and service recommendations for their clientele.

Moreover, big data technology plays a pivotal role in risk management and internal controls within enterprises. Through the development of sophisticated risk assessment frameworks and monitoring systems, big data technology enables enterprises to identify and assess a range of potential risks promptly. This proactive approach provides a robust backbone for the formulation of risk mitigation strategies, ultimately enhancing the resilience and adaptability of enterprises in an ever-changing business landscape. Furthermore, big data technology can also monitor and analyze various business processes within the enterprise in real time, and timely discover and solve operational problems.

In addition, big data technology plays an important role in enterprise innovation decision-making and strategic formulation. By analyzing and mining data from new technologies, products, and markets, big data technology can help enterprises discover new business opportunities and innovation points, providing strong support for formulating innovation strategies and development plans.

Although big data technology has broad application prospects in enterprise decision-making, there are still some problems and challenges. The main issues are the quality of data and privacy protection. Due to the diversity and complexity of big data sources, the quality of data is often difficult to ensure, which brings great uncertainty to data analysis and decision-making. Furthermore, the issue of privacy protection in big data is becoming increasingly prominent, and how to fully utilize the value of big data while ensuring data security has become an urgent problem to be solved.

In the application and development process of big data technology, the research results of different scholars provide important theoretical support and practical guidance for enterprise decision-making.

4 CONSTRUCTION OF OPTIMIZATION ALGORITHMS FOR ENTERPRISE DECISION-MAKING UNDER THE FUSION OF COMPUTER-AIDED AND BIG-DATA

As information technology swiftly progresses and data resources become increasingly abundant, the amalgamation of CAS and Big Data technology has emerged as a pivotal avenue for enhancing enterprise decision-making optimization. The objective of this article is to devise an algorithm that seamlessly integrates CAS with Big Data technology, thereby elevating the precision and efficiency of corporate decisions. In this section, we delve into the intricacies of the algorithm's design principles, framework, and meticulous implementation steps.

4.1 The Necessity Analysis of Integrating Computer-Aided and Big Data

In modern enterprises, CAS provides important technical support for enterprise decision-making with its powerful data processing and information analysis capabilities. However, traditional CAS often relies on fixed models and algorithms, making it difficult to cope with complex and ever-changing business environments. Furthermore, the rise of big data provides new opportunities for optimizing enterprise decision-making. Big data technology can process and analyze massive, diverse, and rapidly changing data, uncover deep information and knowledge hidden behind the data, and provide a more accurate and scientific basis for enterprise decision-making.

Therefore, the effective integration of CAS and big data technology to form a new decision optimization algorithm is of great significance for improving the accuracy of enterprise decision-making. By integrating the data processing capabilities of CAS and the information mining capabilities of big data technology, comprehensive and in-depth analysis and mining of enterprises' internal and external data can be achieved, providing more comprehensive and objective decision support for enterprise decision-makers.

4.2 Design Principles and Framework of Decision Optimization Algorithms

When constructing an enterprise decision optimization algorithm that integrates computer-aided and big data, the following design principles need to be followed:

(1) The principle of comprehensiveness: Algorithms should be able to comprehensively collect, organize, and analyze various data from both internal and external sources of the enterprise, ensuring the completeness and accuracy of the decision-making basis.

(2) Real-time principle: Algorithms should be able to process and analyze data in real time, reflect market dynamics and enterprise operations promptly, and provide decision-makers with the latest decision support.

(3) Scalability principle: Algorithms should have good scalability, be able to adapt to the development and changes of enterprise business, and facilitate subsequent functional expansion and upgrading.

(4) Security principle: Algorithms should ensure the security and privacy protection of data to prevent data leakage and abuse.

Based on the above design principles, this article constructs the following decision optimization algorithm framework:

(1) The Data Acquisition and Pre-treatment Module is tasked with extensively gathering data from both internal and external sources within the enterprise. This includes preprocessing procedures like cleansing, structuring, and converting to maintain data quality and uniformity.

(2) The Advanced Analytics and Insight Extraction Module leverages big data techniques and machine learning algorithms to perform in-depth analysis of the pre-processed data. Its aim is to extract meaningful insights and valuable knowledge.

(3) The Decision Assistance Module integrates and visualizes the outputs from the analysis and mining process, presenting intuitive and easily comprehensible information to aid enterprise decision-makers.

(4) The Ongoing Feedback and Enhancement Module gathers feedback data post-decision implementation. It continuously refines and enhances the algorithm to improve decision accuracy and efficiency.

BPNN, a multi-layer feedforward neural network trained via the backpropagation algorithm, exhibits robust nonlinear mapping capabilities and a strong propensity for self-learning. By developing a BPNN-based risk forecasting model, we can quantitatively scrutinize and anticipate various risks confronting enterprises. This, in turn, equips decision-makers with more holistic and precise decision support.

Within the fundamental framework of decision optimization strategies, the BPNN risk forecasting model seamlessly integrates with components like data aggregation and preprocessing, sophisticated data analysis and insight extraction, intelligent decision assistance, and continuous feedback and enhancement. This integration forms a comprehensive and efficient decision optimization ecosystem.

By extensively analyzing historical and real-time data, the BPNN model identifies a range of potential risks for enterprises, including market, credit, and operational risks, among others. It quantitatively assesses these risks, enabling decision-makers to gain a clearer perspective on the enterprise's risk landscape and, ultimately, make more informed decisions. This article utilizes BPNN as the risk prediction model for optimizing enterprise decisions, as illustrated in Figure 1.

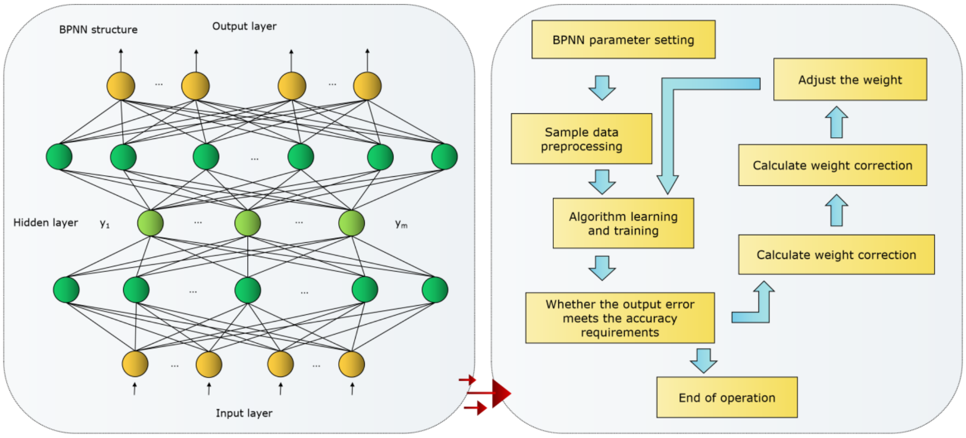

Figure 1: BPNN.

Determine the factor set U and establish the evaluation grade set V for the subject of financial risk assessment.

$$U = \ u_1, u_2, \ldots, u_m \tag{1}$$

$$V = \ v_1, v_2, \ldots, v_m \tag{2}$$

Fuzzy assessment is conducted on every element within U, utilizing the grade index from the evaluation set, thereby deriving the evaluation matrix.

$$R = \ r_{ij} \ _{n\times m} \tag{3}$$

In this context, r_{ij} denotes the extent of membership with v_i. Once the significance index for each factor is ascertained, it is documented as follows:

$$A = \ a_1, a_2, \ldots, a_m \ , \quad \sum_{i=1}^{n} a_i = 1 \tag{4}$$

Synthetic:

$$\bar{B} = AR = \ \bar{b}_1, \bar{b}_2, \ldots, \bar{b}_m \tag{5}$$

Following the normalization process, we obtain:

$$B = \ b_1, b_2, \ldots, b_m \tag{6}$$

Hence, the risk assessment level of the financial appraisal subject can be ascertained.

4.3 Specific Implementation Steps and Technical Details of the Algorithm

(1) Data collection and preprocessing

In the data collection stage, it is necessary to fully utilize the data capture and integration capabilities of CAS to comprehensively collect various data sources from both internal and external sources of the enterprise. These data sources include internal business data, external market data, competitor data, policy and regulatory data, etc. In the data preprocessing stage, it is necessary to clean, deduplicate, and convert the collected data to ensure the quality and consistency of the data. Furthermore, it is needed to normalize the data, eliminate dimensional differences between different data, and facilitate subsequent data analysis and mining.

(2) Data analysis and mining

During the data analysis and extraction phase, utilizing big data technologies alongside machine learning algorithms becomes essential for performing comprehensive data exploration and analysis. Firstly, clustering analysis, association rule mining, and other algorithms can be used to classify and analyze data, discovering the inherent connections and patterns between the data. Secondly, algorithms such as regression analysis and predictive models can be used to predict trends and causal relationships in data, providing a more accurate and scientific basis for enterprise decision-making. In addition, algorithms such as text mining and sentiment analysis can be used to analyze and mine text data, extracting valuable information and knowledge. The data mining architecture of the enterprise decision-making system is shown in Figure 2.

In this article, we will introduce a time-dependent intensity function $\Phi \ t_n$, which is defined as follows:

$$\Phi \ t_n \ = \frac{1}{\alpha} e \int_{t_n}^{t_a} \rho \ t \ dt + \int_{t_n}^{t_a} \theta \ t \ dG \ t \tag{7}$$

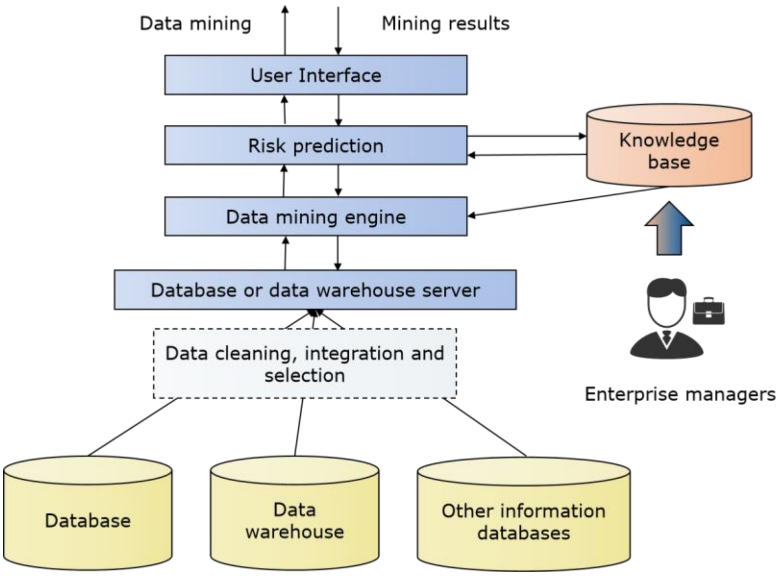

Figure 2: Data mining architecture.

In this context, a represents a time-intensity coefficient that exceeds 0. t_n and denotes the most recent datum within the dataset. t_a signifies a random value within the dataset. $\rho(t)$ and $\theta(t)$ are functions representing drift and volatility, respectively. $G(t)$ refers to a stochastic process. $\rho(t)$ is defined as follows:

$$\rho(t) = \frac{1}{(c+t)^2} \tag{8}$$

In this scenario, c represents the number of samples. As for $\theta(t)$, its definition is outlined below:

$$\theta(t) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{9}$$

In this instance, $\bar{x}$ denotes the mean of the samples, while $G(t)$ representing a stochastic process that satisfies the subsequent criteria:

$$G(0) = 0 \qquad E\left[G(t)\right] = 0 \qquad t>0,\ \ G(t) \sim N(0, \sigma^2 t) \qquad \sigma>0 \tag{10}$$

(3) Decision support

In the decision support stage, the results of analysis and mining need to be integrated and displayed visually to provide intuitive and understandable decision support information for enterprise decision-makers. Furthermore, build a decision support system or platform, integrate and integrate the functions of each module, and provide a one-stop decision support service for enterprise decision makers. By analyzing the externally observed values of the enterprise financial system, we can indirectly acquire its internal state information:

$$\theta_k = f(\theta_{k-1}, v_k) \tag{11}$$

$$y_k = h\left(\theta_k, n_k\right) \tag{12}$$

In this context, θ_k represents the state vector of N_θ -dimension at a time t_k, while y_k denoting the observation vector of t_k -dimension at a time N_y. v_k and n_k, respectively, stand for the state transition noise vector and the observation noise vector.

Utilizing the neural network algorithm, it assesses the documented execution status information and dispatches the evaluation outcomes to the designated mobile device. For clarity, let's consider that each node's value falls within the set {0,1}, specifically:

$$\forall i, j, v_i \in \{0,1\}, h_j \in \{0,1\} \tag{13}$$

The node status of the i visible layer of BPNN is v_i; The state of the j hidden layer node is h_j; The computation of the network state (v,h)'s energy function proceeds as follows:

$$E\left(v,h\middle|\theta\right) = -\sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} v_i W_{ij} h_j \tag{14}$$

In this context, W_{ij} represents the linkage weight connecting the visible node i and the hidden node j. a_i denotes the visible node i's displacement, while b_j signifies the hidden node j's bias. Make a scientific assessment of the prevailing error in the system's fitness value. If this error surpasses the permissible limit, terminate the training process; otherwise, persist with the training until the threshold is attained.

(4) Feedback and optimization

In the feedback and optimization stage, it is necessary to collect feedback information after decision execution and continuously optimize and improve the algorithm. By constructing a feedback mechanism, actual data and performance evaluation information during the decision execution process can be collected, and algorithms can be regularly evaluated and adjusted. Furthermore, online learning algorithms such as A/B testing and multi-arm slot machines can be used for real-time optimization and improvement, improving the accuracy and efficiency of decision-making.

In summary, the enterprise decision optimization algorithm under the integration of computer-aided and big data can achieve comprehensive and in-depth analysis and mining of internal and external data of the enterprise by integrating the data processing capabilities of CAS and the information mining capabilities of big data technology, providing more comprehensive and objective decision support for enterprise decision-makers. By following the design principles of comprehensiveness, real-time performance, scalability, and security, and constructing an algorithm framework that includes modules such as data collection and preprocessing, data analysis and mining, decision support, feedback, and optimization, continuous optimization and improvement of enterprise decision-making can be achieved.

5 EMPIRICAL STUDY

Based on the theoretical construction and technical exploration in the previous text, this section will use empirical research methods to select a representative enterprise as a case and conduct simulation tests on the proposed enterprise decision optimization algorithm under the integration of computer-aided and big data. The purpose of this empirical study is to verify the feasibility, effectiveness, and superiority of algorithms in practical applications, in order to provide more intuitive and powerful technical support and decision-making basis for enterprise decision-makers. Through specific enterprise case analysis, not only can we gain a deeper understanding of the operational logic and application effects of algorithms in practical scenarios, but we can also further explore their adaptability and optimization potential in different enterprise environments and business needs.

In the process of building a BPNN model, parameter selection has a crucial impact on the performance and results of the model. In order to gain a deeper understanding of how these parameters affect the performance of the model, we conducted a series of experiments using the control variable method. Firstly, we investigated the impact of iteration times on the results of the BPNN model. As shown in Table 1, with the increase in iteration times, the performance of the model shows a certain trend of change. When the number of iterations is small, the model may not have fully learned the features of the data, resulting in poor performance; As the number of iterations increases to a certain extent, the performance of the model gradually improves and tends to stabilize.

Iterations	*1*	*6*	*20*	*100*
Hidden layer number	6	6	6	6
Number of hidden layer nodes	70, 50	70, 50	70, 50	70, 50
Error rate	0.1679	0.1554	0.1842	0.2131

Table 1: The impact of different iterations on the results.

Subsequently, we examined how varying the quantity of hidden layers influenced the model's outcomes. The findings are presented in Table 2, illustrating the model's performance with differing numbers of hidden layers. As the count of hidden layers rises, so does the intricacy of the model, enabling it to comprehend more intricate data characteristics. Nevertheless, an excess of hidden layers can hinder the model's trainability and give rise to challenges like gradient vanishing or exploding.

Iterations	*6*	*6*	*6*	*6*
Hidden layer number	3	4	5	6
Number of hidden layer nodes	70	70, 50	70, 70, 50	70, 70, 70, 50
Error rate	0.1678	0.1475	0.1258	0.1579

Table 2: The impact of the number of hidden layers on the results.

Lastly, we conducted an analysis to understand the influence of varying the number of nodes in the hidden layer on the model's outcomes. Table 3 reveals that alterations in the count of hidden layer nodes produce notable effects on the model's efficacy. Having a limited number of nodes might hinder the model's ability to grasp data intricacies fully, whereas a surplus of nodes might result in the model's overfitting. Consequently, determining the optimum number of hidden layer nodes is pivotal for achieving optimal model performance.

Iterations	*6*	*6*	*6*	*6*
Hidden layer number	6	6	6	6
Number of hidden layer	70, 50, 50	50, 50, 70	70, 50, 50	220, 160, 50

nodes				
Error rate	0.1533	0.1547	0.1361	0.2655

Table 3: The impact of the number of hidden layer nodes on the results.

In Figure 3, a comparison was observed between the output of risk prediction data and the real financial risk data. The model has shown satisfactory performance in predicting risk data, and its prediction results can converge well to real data, which means that the model has made good approximations and fits the original data.

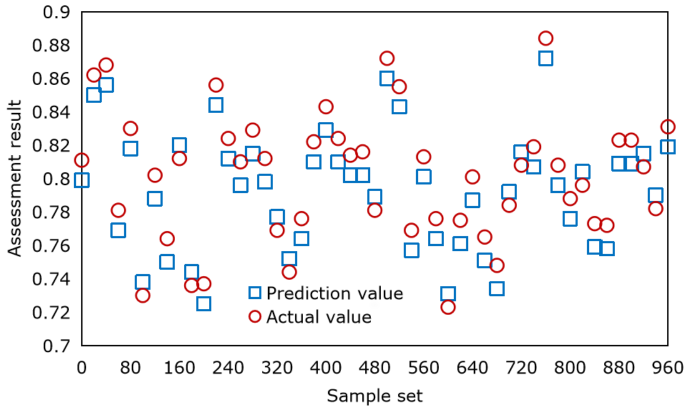

Figure 3: Model learning results.

By comparing the performance of the financial risk prediction model and SVM algorithm in terms of accuracy and mean absolute error (MAE) in this article, some important conclusions can be drawn from Figures 4 and 5.

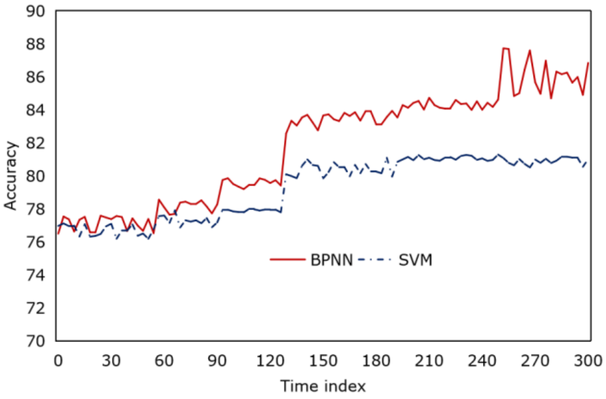

Figure 4: Accuracy comparison.

From the perspective of accuracy, the financial risk prediction model proposed in this article is significantly superior to the SVM algorithm. As the number of iterations increases, the accuracy of our method gradually improves and stabilizes at a higher level, while the accuracy of the SVM algorithm is relatively low. Specifically, the accuracy of our method is 20.01% higher than that of the SVM algorithm, indicating that our method has a stronger ability to identify financial risks.

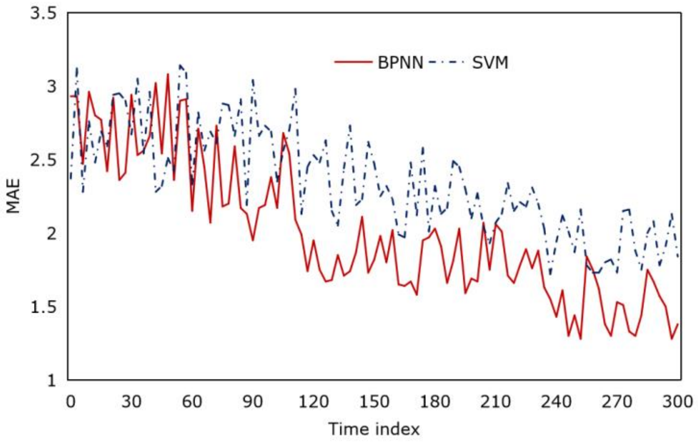

Figure 5: Comparison of MAE.

From the perspective of error, the method proposed in this article also performs well. Figure 5 shows the MAE changes of two methods during multiple iterations. The MAE of this method is significantly lower than that of the SVM algorithm, with an error reduction of 42.77%. This means that the method proposed in this article can more accurately approximate the true value when predicting financial risks, reduce prediction errors, and thus improve the reliability of decision-making.

In order to solve the overfitting problem of the BPNN model, this article introduces a dropout layer after each hidden layer of the BPNN. Dropout is a regularization technique that randomly "closes" or "discards" some hidden layer neurons and their corresponding connection weights during the training process with a certain probability. This can effectively prevent the model from overfitting the noise and outliers in the training data, and improve the model's generalization ability. After introducing the dropout layer, the BPNN model randomly selects a portion of neurons for computation during each forward propagation process, which makes the model slightly different in each iteration. This randomness helps to reduce the complex co-adaptability between neurons, making the model more robust and less susceptible to small changes in training data. Figure 6 shows the false alarm rate of the financial risk prediction model.

The false alarm rate of the method in this article is significantly lower than that of the SVM algorithm. The false alarm rate refers to the proportion of models that mistakenly predict risks when there is no actual risk. A lower false alarm rate means that the model can more accurately identify real risk events, reducing unnecessary false alarms and interference. The reason why this method can achieve a lower false alarm rate is not only due to the effective application of the dropout layer but also related to the overall design and optimization of the model. Through in-depth analysis and feature extraction of financial risk data, this method can more accurately capture the essential characteristics of risk events and reduce the possibility of misjudgment.

Fine-tuning the entire network is a common strategy when faced with large and similar new datasets. Fine-tuning can utilize the knowledge of pre-trained models and make adaptive adjustments to new datasets, thereby improving the performance of the model on new tasks. Figure 7 shows the stability results of the model. The stability of BPNN is significantly higher than other methods. The stability of a model refers to its ability to maintain relatively consistent predictive performance in the face of different data or small data changes.

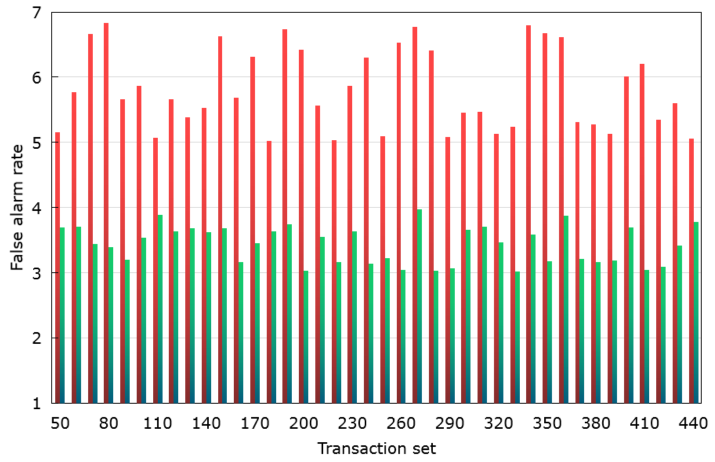

Figure 6: Comparison of false alarm rate.

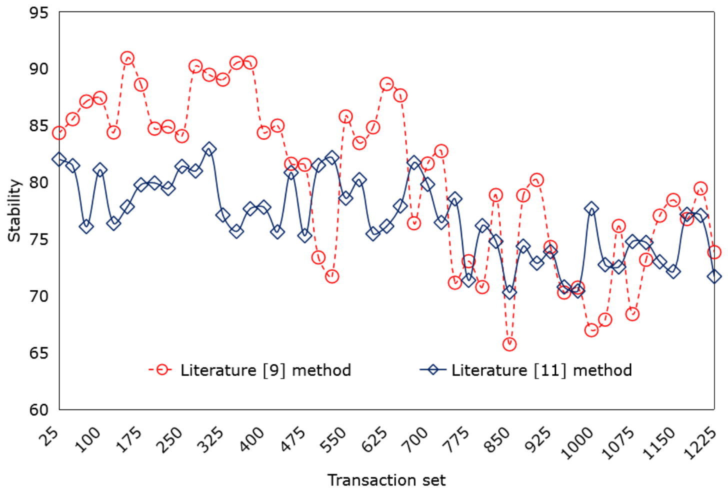

Figure 7: Comparison of model stability.

The reason why BPNN can achieve high stability is mainly due to its powerful learning and generalization capabilities. Through the backpropagation algorithm, BPNN can automatically adjust the weights and biases of neurons to adapt to the features of new datasets. Meanwhile, due to the similarity between the new dataset and the pre-training dataset, BPNN can fully utilize the useful features learned during the pre-training process, accelerate the fine-tuning process, and improve the stability of the model.

6 CONCLUSION

In this era of a closely connected global economy, enterprises must face increasingly complex and changing business environments and competitive situations while embracing a broader market. CAS, with its powerful data processing and information analysis capabilities, has become a powerful assistant for enterprise decision-making.

This article aims to solve financial risk prediction problems by constructing and optimizing BPNN models and comparing and analyzing them with traditional SVM algorithms. Through in-depth research and experimental verification, it was found that the BPNN model proposed in this article has shown significant advantages in multiple aspects. In terms of model design, this article innovatively introduces dropout layers after each hidden layer of BPNN, effectively solving the problem of overfitting. The application of the Dropout layer enables the model to randomly discard some neurons during the training process, enhancing the model's generalization ability and robustness. The method presented in this article demonstrates a substantial improvement in accuracy, surpassing the SVM algorithm by 20.01%. Furthermore, it achieves a notable reduction in error by 42.77%. This result indicates that the BPNN model constructed in this article has a stronger recognition ability and higher prediction accuracy in financial risk prediction tasks. In terms of model stability, BPNN has significantly higher stability than other methods, which means that the model constructed in this article can operate more stably in practical applications, providing more reliable support for financial risk management.

In summary, this article has successfully constructed an efficient and accurate financial risk prediction model by introducing dropout layers, optimizing model design, and adjusting parameters. In the future, we will further explore and study how to apply this model to a wider range of financial scenarios to better serve practical business needs.

7 ACKNOWLEDGEMENT

This work was supported by Key Project of Humanities and Social Sciences Research in Colleges and Universities in Anhui Province, Analysis of the Spatiotemporal Coupling and Influencing Factors of Digital Economy and High-quality Development in the Yangtze River Delta Region (2023AH050394); General Project of Humanities and Social Sciences Research in Fuyang City (Suzhou-Fuyang Joint Project), Empirical Research on the Impact of Digital Economic Development on Employment in Fuyang (FYSK2022LH02).

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