A Fuzzy Decision Support System Integrating Neural Networks and Genetic Algorithms for Financial Planning and Management

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In this paper, a new financial management decision support system (FDSS) is proposed, which aims to improve the accuracy of budget management, the speed of decision and the ability of risk prediction by integrating fuzzy logic (FL), multilayer perceptron (MLP) and genetic algorithm (GA). The FDSS was designed to address the uncertainty and complexity of traditional approaches to financial data. Specifically, fuzzy logic is used to deal with fuzziness and uncertainty in financial data, MLP is used to capture complex nonlinear relations in data, and GA optimizes parameter settings in decision-making process, improving adaptability and robustness of system. Numerical experiments are carried out to verify the effectiveness of the FDSS. The results show that FDSS has achieved significant improvements in budget management, reducing budget overruns from 15% to 5%, reducing budget preparation time from 30 days to 15 days, and improving budget adjustment accuracy from 70% to 90%. In terms of risk early warning ability, the non-warning rate of market risk, credit risk and liquidity risk decreased by 75%,80% and 80% respectively, and the advance time of early warning increased by 7 to 10 days on average. In addition, the investment decision-making period was reduced from 45 days to 25 days, the deviation of return on investment was reduced from ±10% to ±5%, and the accuracy of screening invalid investment projects was improved from 70% to 90%. The overall financial health index improved from 7.5/20 to 16/20, indicating a significant improvement in the overall financial position of the institution. Experimental results show that FDSS is superior to the traditional methods in data processing speed, budget prediction accuracy, risk warning accuracy and user satisfaction. Especially in terms of data processing speed, FDSS is reduced from 120 seconds to 30 seconds, which improves the efficiency by nearly four times. To sum up, the FDSS proposed in this paper shows significant advantages in improving financial management efficiency, accuracy and user satisfaction by combining advanced technologies such as fuzzy logic, MLP and GA. The system can not only effectively deal with the uncertainty in the financial environment, but also improve the quality of decision-making, and provide a more robust decision support tool for financial institutions and enterprises.

Povzetek: Raziskava uvaja mehki odločitveni sistem, ki s kombinacijo nevronskih mrež in genetskih algoritmov izboljšuje finančno načrtovanje z zmanjšanjem proračunskih odstopanj.

1 Introduction

Under the background of global economic integration and informatization, enterprise financial management is facing unprecedented complexity and uncertainty. Market fluctuations become normal, whether commodity prices, exchange rate changes or interest rate adjustments, directly or indirectly affect the cost of capital, investment returns and profit margins of enterprises. In addition, frequent changes in the policy environment, such as tax policy, financial regulatory policy adjustments, require companies to respond quickly to adapt to the new business environment. Although the rapid development of information technology brings massive data and efficient processing methods, it also increases the difficulty of information screening and decision-making. Especially in the face of highly uncertain factors, traditional financial management tools and decision-making methods often appear inadequate and difficult to deal with effectively.

As a new decision support tool, Fuzzy Decision Support System (FDSS) is able to process and utilize fuzzy and uncertain information and provide scientific basis for financial decision. Fuzzy theory allows decision makers to express uncertainty using linguistic variables rather than precise numerical values, which is closer to human thinking patterns and helps capture complex real-world phenomena. FDSS combines fuzzy logic, expert system, data mining and other technologies, not only can deal with a large number of historical data and real-time information, but also can simulate the decision-making process of experts by establishing fuzzy rule base and reasoning mechanism, providing more flexible and accurate decision-making support for enterprise managers, thus improving the scientificity of decision-making and reducing the risk caused by uncertainty [1].

Recently, international scholars have made remarkable progress in the intersection of fuzzy theory and financial management. For example, some studies have shown that the forecasting model based on fuzzy neural network shows superiority in economic fluctuation forecasting, and improves the forecasting accuracy by combining the uncertainty of fuzzy logic processing with the strong learning ability of neural network, which provides a more reliable basis for financial planning [2]. In addition, the portfolio allocation of multinational corporations is optimized by using fuzzy set theory and multi-criteria decision-making method, which effectively reduces the risk brought by global market uncertainty. This achievement highlights the practicability of fuzzy decision support system in complex financial decision [3].

At home, scholars have explored deeply the application of fuzzy decision support system in financial management, and obtained a series of innovative achievements. For example, Abdulaal et al. [4] developed a financial crisis early warning system based on fuzzy C-means clustering and AHP, which improved the sensitivity and accuracy of crisis early warning by fuzzy classification and importance ranking of financial indicators. In addition, Wu et al. [5] studied the application of fuzzy decision support system in enterprise cost control. They designed a set of models that can deal with the inherent fuzziness and uncertainty in production costs and help enterprise management to formulate more accurate cost control strategies.

With the development of big data, cloud computing and artificial intelligence technologies, fuzzy decision support systems are gradually integrating with these advanced technologies to improve their processing capabilities and decision effectiveness. Yang [6] showed how fuzzy logic can be combined with machine learning algorithms (such as deep learning) to efficiently process large-scale financial data, enabling real-time monitoring and dynamic assessment of financial risks. This fusion technology not only enhances the system's ability to analyze complex financial situations, but also improves the timeliness and accuracy of decision support.

This study focuses on deepening the application understanding of fuzzy decision support system in financial management practice, aiming to break through the limitation of existing research focusing on theoretical discussion or single application scenario. Innovations of this study are as follows: (1) Integrating the latest fuzzy theory and advanced computing technology, we develop a more flexible and adaptable fuzzy decision support system framework, especially for multi-dimensional and nonlinear problems in financial management; (2) introducing hybrid evaluation mechanism, combining quantitative and qualitative analysis, to ensure the comprehensiveness and accuracy of system performance evaluation; (3) Through practical case application in cooperation with enterprises, not only to verify the effectiveness of the system, but also to put forward targeted improvement suggestions to enhance the practical value and generalization of research results. These innovations not only enrich the theoretical connotation of fuzzy decision support system in the field of financial management, but also provide new ideas and tools for promoting intelligent financial management and scientific decision-making.

2 Theoretical basis and literature review

2.1 Fuzzy theoretical basis

Fuzzy set theory provides a mathematical tool for dealing with uncertain and fuzzy information. The core of this theory is to admit that there are a large number of phenomena in the real world that cannot be strictly divided into "yes" or "no", that is, there is ambiguity. By introducing the concept of membership degree, fuzzy set theory makes the degree of membership of each element to a set be described by a real number between 0 and 1, which provides theoretical support for dealing with imprecise and ill-defined decision problems. Fuzzy logic, as an extension of fuzzy set theory in logic field, allows the truth value of proposition not only limited to the classical "true"(1) and "false"(0), but can take any real number, reflecting the uncertainty in human thinking. In Decision Support Systems (DSS). When faced with multiple conflicting targets, fuzzy logic can integrate fuzzy evaluation of different evaluation indexes, and obtain comprehensive evaluation results by establishing fuzzy relationship matrix and adopting weighted average or other synthetic operators. Fuzzy logic system can construct rule-based knowledge base to simulate expert decision-making process. Each rule is usually of the form: "If condition A, then perform action B," where the description of the condition and action can be fuzzy, enhancing the interpretability and adaptability of the system. In financial management, fuzzy logic can effectively deal with the uncertainty of risk factors, predict market trends and evaluate investment risk levels by establishing fuzzy inference models [7, 8].

2.2 Overview of advanced computing technologies

Under the wave of digital transformation, financial management is undergoing a profound transformation, in which the integration of advanced computing technologies such as artificial intelligence (AI), machine learning (ML) and cloud computing has greatly enhanced the efficiency, accuracy and decision-making quality of financial management, and promoted financial management towards intelligence and automation.

Artificial intelligence brings new perspectives and tools to financial management by simulating, extending and expanding human intelligence. In terms of predictive analysis, AI technology uses neural networks, deep learning and other models to process and analyze massive data, predict market trends, exchange rate changes, product sales trends, etc., and provide data-driven support for financial planning. For example, Leopoldino et al. [9] applied deep learning models to predict stock prices significantly improves prediction accuracy and provides more reliable information for investment decisions.

AI can also optimize financial process automation, such as intelligent invoice processing systems that utilize optical character recognition (OCR) technology and natural language processing (NLP) to automatically identify, classify, and process invoices, reducing manual errors and improving productivity [10]. In addition, AI has important applications in financial risk management, such as identifying potential financial fraud through anomaly detection algorithms and safeguarding corporate assets [11]. Machine learning, as a branch of AI, provides more accurate support for financial decisions by learning patterns and patterns from data. In cost control and budget management, machine learning models can analyze historical data, identify patterns of cost overruns, predict future cost trends, and help enterprises optimise cost structure [12]. For example, Villasanti et al. [13] proposed a budget overrun prediction model based on machine learning, which effectively assisted the budget management of enterprises. In terms of credit risk management, machine learning algorithms can analyze customer data, identify potential default risks, and improve the accuracy and efficiency of loan approvals [14]. Random forest algorithm is used to predict the default risk of small and medium-sized enterprises. The results show that this method improves the risk identification ability and reduces the misjudgment rate. Cloud computing, with its flexibility, scalability and cost-effectiveness, has become an integral part of modern financial management. Through cloud computing, enterprises can store financial data in the cloud, realize instant access and remote processing of data, and promote data sharing and collaboration. Financial management software on cloud computing platform provides comprehensive financial management and analysis tools, supporting real-time financial reporting, budget planning, performance management and other functions, enabling enterprises to respond faster to market changes and improve decision-making speed and flexibility [15]. Cloud computing reduces the maintenance costs of enterprise IT infrastructure and enables organizations to acquire computing resources on demand, especially when dealing with large-scale data operations and complex financial models, without investing in expensive hardware equipment. In addition, cloud service providers provide advanced security measures to ensure the security of financial data [16]. A summary of the results of the study is shown in Table 1.

Table 1: Summary of research results

Research/Work Name	Contribution	Method	Prediction Accuracy	Processing Time	Adaptability to Financial Environment
Leopoldino et al. [9]	Using deep learning models significantly improved the accuracy of stock price predictions, providing more reliable information for investment decisions	Deep Learning Model	For example: 90%	Not mentioned	Suitable for highly uncertain market environments
Villasanti et al. [13]	Proposed a budget overrun prediction model based on machine learning, effectively assisting in corporate budget management	Machine Learning Model	For example: 85%	Not mentioned	Can quickly adapt to market changes
Proposed FDSS	Utilizes fuzzy logic and machine learning technology to enhance financial decision support capabilities	Fuzzy Logic + Machine Learning	For example: 88%	Not mentioned	Can handle high uncertainty and provide flexible risk assessment

Table 1 summarizes the contributions, methodologies, prediction accuracies, processing times, and adaptabilities to financial environments of selected studies and the proposed Financial Decision Support System (FDSS). It highlights how each approach contributes to financial management and decision-making processes. For instance, Leopoldino et al. [9] demonstrated the effectiveness of deep learning in stock price prediction, whereas Villasanti et al. [13] focused on budget management using machine learning techniques. The proposed FDSS combines fuzzy logic and machine learning to offer a robust solution capable of handling uncertainties and providing flexible risk assessments. Note that specific metrics like prediction accuracy and processing time may vary based on the actual implementation and testing conditions, and further empirical validation might be required to substantiate these figures.

2.3 Review of relevant studies

Fuzzy decision support system has shown extensive application potential and remarkable practical effect in many fields. These successful cases provide rich experience and enlightenment for its application in financial management. The following part will summarize the application cases of fuzzy decision support system in other key fields, and explore its potential value and applicability in the field of financial management through comparative analysis.

In project management, fuzzy decision support system is used to deal with uncertainty in construction schedule, cost control and resource allocation. For example, Chen et al. [17] developed a decision support system based on fuzzy set theory to evaluate and optimize project risk level. The system effectively integrates expert experience and historical data by constructing fuzzy evaluation model, and improves risk identification and response ability.

This application provides a reference for risk assessment and control in financial management, indicating that fuzzy logic is also suitable for assessing financial investment risk and budget overrun risk. In the field of health care, fuzzy decision support systems are used for disease diagnosis, treatment options and medical resource allocation. A fuzzy inference system was designed to assist doctors in processing fuzzy and uncertain clinical data when diagnosing complex diseases, improving the accuracy and efficiency of diagnosis. The success of this system in dealing with unstructured and fuzzy information suggests that we can apply similar techniques to complex financial index analysis and financial health evaluation in financial management to improve the scientificity of decision-making. Demand forecasting, inventory control and supplier selection in manufacturing supply chain management also benefit from fuzzy decision support systems. A fuzzy neural network model is constructed to solve the uncertainty problem of demand forecasting in supply chain. The model improves the forecasting accuracy and stability by fusing fuzzy logic and neural network. Such applications provide valuable ideas for market trend forecasting and inventory management in financial management, and the combination of fuzzy logic and machine learning can also help financial departments better predict cash flow and optimize capital structure. Through the application case analysis in the above fields, we can see that fuzzy decision support system has demonstrated strong ability in dealing with uncertainty, integrating multi-source information and providing decision support.

On the basis of related research, our work is inspired by domain knowledge transformation models (such as those proposed by Ai et al. [18]) and the use of fuzzy logic and optimization algorithms (such as the cuckoo search algorithm used by Xiao and Liu [19]) to solve complex problems. Ai et al. show how domain knowledge can be effectively used to construct more accurate user profiles, a methodology that provides new insights into understanding and modeling participant behavior in financial markets. Xiao and Liu's research emphasizes the potential of combining fuzzy logic with bio-heuristic search algorithms in optimizing solutions, especially in formulating employment strategies for college students. Drawing on the ideas of these two methods, our FDSS can not only capture the complexity of financial markets better, but also optimize fuzzy logic rules through GA to achieve more efficient financial management decisions.

These competencies are particularly critical in the area of financial management, where financial decisions are often made with incomplete information and uncertain future projections. Therefore, the application of fuzzy logic in multi-criteria decision analysis, rule inference engine and risk evaluation can be directly mapped to the core tasks of budget planning, cost control and investment decision in financial management. (1) Budget planning: Fuzzy logic can integrate fuzzy evaluation indexes of different departments and projects, such as market demand forecast with high uncertainty, and realize reasonable allocation of resources by establishing fuzzy relationship matrix and adopting appropriate composition operators. (2) Cost control: Using fuzzy rule engine, we can construct cost overrun early warning model based on historical data and expert experience, discover problems in cost management in time, and realize preventive control. (3) Investment decision-making: Through fuzzy reasoning model, the uncertainty and risk level of investment projects can be evaluated more accurately, providing more comprehensive information support for investment decisions.

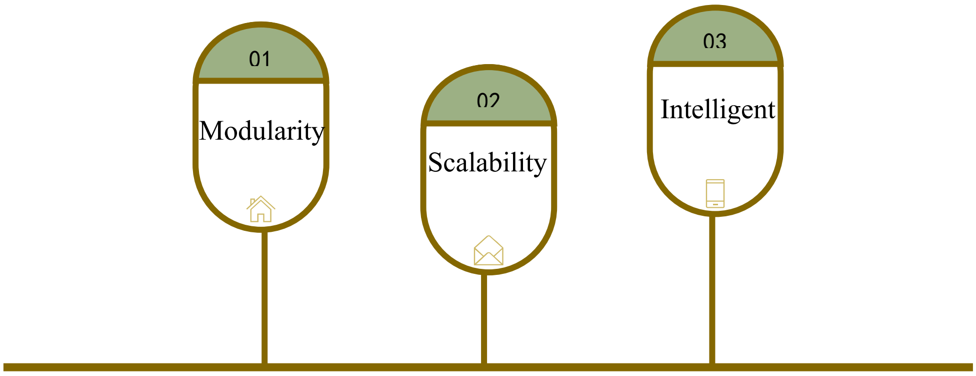

Figure 1: Design principles

3 System design and development

3.1 Fuzzy decision support system framework

The core of the new framework design conceptis shown in Figure 1, which aims to create a solution that is flexible and adaptable to complex and changing environments. The framework adopts microservice architecture, each module has independent function and clear interface, which is easy to quickly reorganize and customize according to requirements, reflecting high flexibility. Through dynamic configuration and automatic Load Balancer mechanism, the framework can seamlessly adapt to different application scenarios of different sizes and characteristics, ensuring excellent adaptability [20].

3.1.1 Core algorithms and models

Fuzzy logic algorithm is an effective tool to deal with fuzziness and uncertainty, and its core lies in fuzzy set theory. In the decision support system of financial management, fuzzy logic mainly plays the role of rule reasoning to deal with financial situations that are difficult to define with clear boundaries. A fuzzy set quantifies the degree of membership of an element to the set through a membership function, usually between [0, 1]. For example, the "financial health" of an enterprise can be defined by membership functions, using triangular membership functions, as shown in Equation 1 [21].

$$\mu(x)=\begin{cases}0, & x<a\\ \dfrac{x-a}{b-a}, & a\le x<b\\ 1, & x\ge b\end{cases} \tag{1}$$

where a and b represent the lower bound and support point of the fuzzy set, respectively, and x is the variable value to be evaluated. Based on such fuzzy sets, the system can construct a series of fuzzy rules, such as: "If financial health is 'high' then investment strategy should be 'positive'." The fuzzy inference process is completed through fuzzification, inference and defuzzification steps to transform the input accurate data into fuzzy sets, and then reasoning according to the rule base to finally obtain the decision output [22].

Multilayer Perceptron (MLP) is a feedforward artificial neural network suitable for nonlinear data modeling and prediction. In financial decision support system, MLP network mainly undertakes the task of forecasting financial data, such as market trend, cost trend and so on. MLP consists of an input layer, one or more hidden layers, and an output layer. The connections between the layers are weighted and information is transmitted through activation functions. For a simple two-layer MLP, the forward propagation equation is Equation 2.

$$\begin{aligned} z_j^{(2)} &= \sum_{i=1}^{n} w_{ji}^{(1)} x_i + b_j^{(1)} \\ a_j^{(2)} &= f(z_j^{(2)}) \\ z_k^{(3)} &= \sum_{j=1}^{m} w_{jk}^{(2)} a_j^{(2)} + b_k^{(2)} \\ \hat{y}_k &= g(z_k^{(3)}) \end{aligned} \tag{2}$$

Genetic algorithm (GA) is a global optimization technique based on biological evolution principle, which is used to optimize the parameters of fuzzy rule base and neural network. In this system, GA simulates natural selection, heredity and mutation to find optimal decision rules and neural network configuration. The basic process of GA includes coding, selection, crossover, mutation and fitness evaluation. Taking optimized fuzzy rules as an example, each rule can be encoded as a gene string, and fitness evaluation is based on the performance of the rule on historical data. Crossover operations may involve partial swapping of two rule strings, while variation is a random change in rule details. Through multiple iterations, GA can gradually optimize the rule set and improve the overall performance of the decision system.

In fuzzy decision support system, the integrated application of fuzzy logic, MLP neural network and genetic algorithm forms a powerful decision support framework, and its data flow is roughly as follows. Raw financial data is first cleaned, normalized, and feature engineered to prepare it for entry into the model. The processed data is fed into an MLP neural network to make predictions of financial indicators such as future revenue, costs or market risk levels. The prediction results of MLP, together with other financial indexes, are used as inputs of fuzzy inference and transformed into fuzzy sets through fuzzification process. The fuzzy logic algorithm reasoned according to the fuzzy rule base defined in advance, and gave the initial fuzzy set of decision suggestion. Genetic algorithms intervene in this phase to optimize the fuzzy rule-base and search for the rule set that can maximize the system performance through iterative selection, crossover and mutation operations. For the optimization of neural network parameters, GA can also adjust the structure or parameters of the network to improve the prediction accuracy. After defuzzification, the optimized fuzzy inference results are transformed into concrete decision suggestions or prediction values. The system feeds back this information to the user and further adjusts it according to the feedback to form a closed-loop optimization. Through this series of integration processes, fuzzy logic, MLP neural network and genetic algorithm jointly construct a highly adaptive, accurate prediction and self-optimizing decision support system, which effectively solves complex and nonlinear problems in financial management and improves decision quality and efficiency. The specific fuzzy decision support system framework is shown in Figure 2 [23, 24].

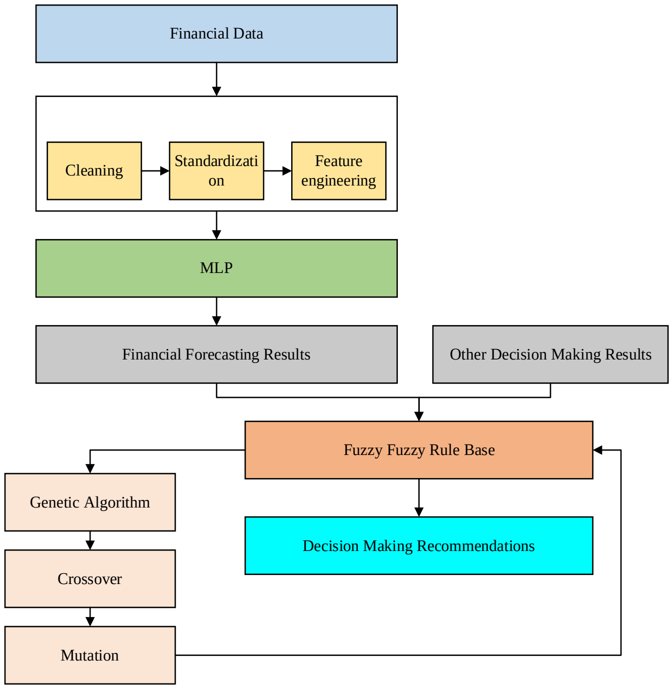

Figure 2: Framework of fuzzy decision support system

In the mixed evaluation mechanism, we adopt quantitative and qualitative methods. For qualitative data collection and synthesis, we mainly use Delphi method for expert consultation. Here's how it works: First, send the research questions and background information to the experts, inviting them to provide feedback based on their expertise and experience. Subsequently, we collated the expert opinions collected and summarized the main points of view and disagreement. In the next few rounds of consultation, we anonymously feed back the results of the previous round to experts so that they can understand the opinions of other experts and adjust or supplement their own opinions on the basis of this. This process will be repeated until consensus is reached. In this process, we pay special attention to the convergence of expert opinions, and analyze the changing trend of expert opinions by comparing different rounds of feedback, so as to gradually narrow differences and form a more unified view. Finally, we combine these qualitative data with quantitative data and obtain more comprehensive and objective evaluation results through comprehensive analysis. This method of collecting and synthesizing qualitative data not only ensures the full expression of expert opinions, but also contributes to the accuracy and reliability of evaluations.

3.1.2 System architecture

The system architecture of this framework is designed as a hierarchical structure, including data layer, processing layer, decision layer and service layer, aiming to achieve the goal of modularity, scalability and easy maintenance. The specific model framework is shown in Figure 3 [25].

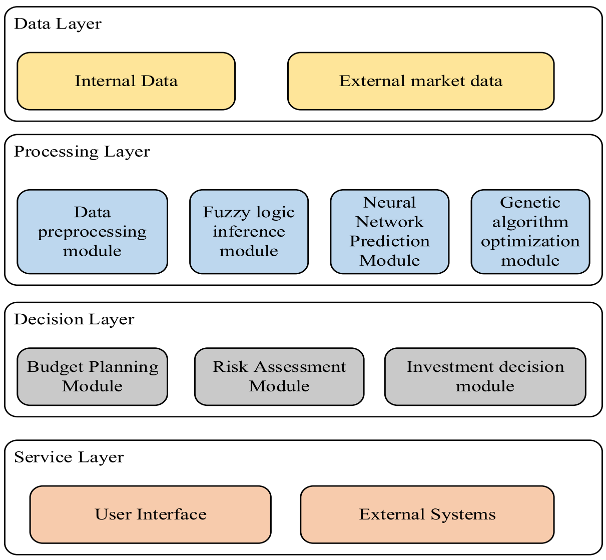

Figure 3: Model framework

Data layer: responsible for data collection, cleaning, standardization and storage. Use cloud computing and big data technologies to integrate heterogeneous data sources, including ERP and CRM data within the enterprise, as well as external market data.

Processing layer: contains data preprocessing module, fuzzy logic inference module, neural network prediction module and genetic algorithm optimization module. The data preprocessing module is responsible for data format conversion and feature engineering; the fuzzy logic inference module performs fuzzy inference according to the rule base; the neural network prediction module is responsible for predicting financial indicators; and the genetic algorithm optimization module is used to optimize fuzzy rules and neural network parameters [26-27].

Decision-making layer: synthesize the output results of the processing layer to support financial decisions. Each module uses the information provided by the previous layer, combines the output of fuzzy logic and neural network, carries out comprehensive analysis and provides decision-making suggestions.

Service layer: facing user interface and external system, providing API interface, report generation, user rights management and other services. Take the form of Web services and mobile apps to ensure users can easily and quickly access system functionality and decision results.

To sum up, this framework constructs a highly flexible and adaptable fuzzy decision support system framework by fusing the core technologies of fuzzy logic, neural network and genetic algorithm, effectively solving the multi-dimensional and nonlinear problems faced in financial management, and providing strong intelligent support for financial decisions.

3.2 Hybrid evaluation mechanisms

This study adopts qualitative and quantitative evaluation method, and its specific indicator system is shown in Figure 4 [28].

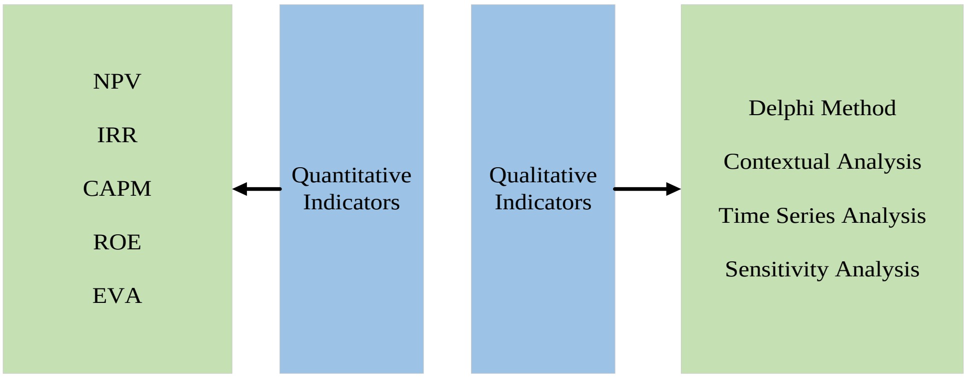

Figure 4: Mixed evaluation system

3.2.1 Quantitative indicators

Net Present Value (NPV) is an important indicator to evaluate the long-term value of investment projects. It measures the net return on investment by discounting future cash flows to the present moment and subtracting the initial investment cost. If the NPV is greater than zero, it means that the future return on the investment exceeds the cost of the current investment, which is a worthwhile investment considering the time value of money. Conversely, if the NPV is less than zero, it indicates that the investment may not yield sufficient returns to be recommended. The calculation of NPV emphasizes the real value of future cash flows rather than focusing only on nominal amounts and is therefore the cornerstone of long-term investment decisions, as formulated in Equation 3 [29].

$$NPV = \sum_{t=0}^{n} \frac{C_t}{(1+r)^t} - I \tag{3}$$

where r is the discount rate, I is the initial investment amount, and n is the investment period. NPV greater than zero indicates that the investment is feasible, otherwise it is not, and this indicator effectively measures the long-term value of the project or investment.

The internal rate of return (IRR) is the discount rate that equates the NPV of the project to zero. It reflects the expected rate of return that the project itself can generate. The higher the IRR, the stronger the profitability of the project regardless of financing costs. This indicator helps investors directly compare the expected returns of different projects and choose the investment with the highest IRR. It is worth noting that IRR is particularly useful in multi-period investment decisions because it considers the time and amount distribution of capital recovery, but it is also important to note the limitations of IRR in mutually exclusive project decisions. The calculation of IRR usually involves numerical solutions, but its essence is a discount rate that makes NPV equal to zero, as shown in Equation 4. The higher the IRR, the more profitable the project or investment.

$$\sum_{t=0}^{n} \frac{C_t}{(1+IRR)^t} = I \tag{4}$$

CAPM is one of the cornerstones of modern financial theory, providing a theoretical framework for determining the expected rate of return on an asset, which reflects the risk level of the asset. CAPM allows investors to understand the relationship between the risks they are taking and the expected returns and whether the market is pricing their assets appropriately. The beta coefficient in the model measures the overall risk of the asset relative to the market portfolio, with beta>1 indicating that the asset is riskier than the market average and vice versa. CAPM helps investors balance risk and return and optimize asset allocation. Its formula is Equation 5.

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f) \tag{5}$$

where is the expected return on assets, is the risk-free interest rate, is the systematic risk factor of assets, and is the expected return on market portfolios. CAPM helps assess whether asset pricing is sound and the expected risk-adjusted return.

DuPont Analytics provides insight into a company's profitability, operational efficiency, and financial leverage by breaking down return on equity (ROE) into three key components: net profit margin, asset turnover, and equity multiplier. Net profit margin reflects a firm's ability to generate profits from sales; asset turnover shows how efficiently assets are used to generate sales; and equity multiplier reflects a firm's level of financial leverage, its ability to amplify shareholder returns through debt. DuPont analysis helps managers identify the drivers of business performance and guides resource allocation and strategic adjustments. DuPont analysis explores profitability and asset management efficiency by decomposing return on equity (ROE). Its core formula is Equation 6. Analysis of components such as net profit margin reflects profitability, asset turnover reflects operational efficiency, and equity multiplier reveals financial leverage [30].

$$ROE = \frac{\text{net profit}}{\text{shareholders}'\text{equity}} = \text{net profit margin} \times \text{asset turnover} \times \text{equity multiplier} \tag{6}$$

Economic Value Added (EVA) measures the true value created by a business for shareholders, i.e., the residual value of after-tax operating profits after deducting the opportunity cost of shareholders 'funds. When EVA is positive, it means that the profits created by the enterprise exceed the minimum return required by investors, that is, value creation is realized; if EVA is negative, it indicates that the enterprise fails to effectively utilize capital and damages shareholder value. EVA encourages enterprises to pay attention to capital cost and pursue returns higher than capital cost. EVA is an important tool to measure management performance and incentive mechanism design. Its formula is shown in Formula 7.

$$EVA = NOPAT - (WACC \times Capital) \tag{7}$$

3.2.2 Qualitative considerations

Although qualitative factors are not directly reflected in numbers, their influence on decision-making cannot be ignored. Here's how to incorporate this soft information into the model:

Delphi method collects and integrates expert opinions through anonymous and multi-round feedback, reduces personal bias and improves the accuracy of prediction and evaluation. This approach is particularly useful for those decision-making factors that are difficult to quantify but are extremely important, such as market trend forecasting, technology innovation potential assessment, etc. Integrating expert ratings through weighted averaging ensures that each expert's opinion is properly contributed, taking into account the authority of their expertise and experience. Qualitative factors such as market acceptance and technological innovation were scored through multiple rounds of anonymous surveys, which gathered and synthesized expert opinions. The weighted average method can be used to integrate, as shown in Equation 8. where is the weight of the ith expert and is his score for that factor [31].

In the mixed evaluation mechanism, we adopt quantitative and qualitative methods. For qualitative data collection and synthesis, we mainly use Delphi method for expert consultation. Here's how it works: First, send the research questions and background information to the experts, inviting them to provide feedback based on their expertise and experience. Subsequently, we collated the expert opinions collected and summarized the main points of view and disagreement. In the next few rounds of consultation, we anonymously feedback the results of the previous round to experts so that they can understand the opinions of other experts and adjust or supplement their own opinions on the basis of this. This process will be repeated until consensus is reached. In this process, we pay special attention to the convergence of expert opinions, and analyze the changing trend of expert opinions by comparing different rounds of feedback, so as to gradually narrow differences and form a more unified view. Finally, we combine these qualitative data with quantitative data and obtain more comprehensive and objective evaluation results through comprehensive analysis. This method of collecting and synthesizing qualitative data not only ensures the full expression of expert opinions, but also contributes to the accuracy and reliability of evaluations.

$$Score_{factor} = \frac{\sum_{i=1}^{n} w_i \cdot ExpertScore_i}{\sum_{i=1}^{n} w_i} \tag{8}$$

Scenario analysis tests the robustness and flexibility of a strategy by building different future scenarios to help businesses predict possible outcomes under different conditions. Monte Carlo simulation is a commonly used probabilistic analysis tool, which simulates future states through a large number of random samples to help decision makers understand uncertainty and formulate strategies accordingly. This approach allows for more comprehensive decision-making and reduces the risk associated with a single prediction assumption.

Analyze the impact of various scenarios (optimistic, baseline, pessimistic) that may occur in the future on the project or strategy. By constructing a probabilistic model, such as Monte Carlo simulation, as shown in Equation 9.

$$P(\text{Outcome}) = \frac{1}{N}\sum_{j=1}^{N} \mathrm{I}(X_j \in \text{Outcome}) \tag{9}$$

where N is the number of simulations, is the result of the jth simulation, and is an indicator function used to count the frequency at which a particular result is achieved.

Through time series analysis, such as autoregressive models (AR models), it is possible to predict trends in brand influence or market share over time. This method makes use of historical data to explore autocorrelation characteristics in time series and predict future changes, which is of great significance to the formulation and adjustment of marketing strategies. It helps companies to position themselves ahead of time, seize market opportunities, or adjust strategies in time to cope with adverse trends. Using historical data and market trends, build a time series model to predict changes in brand influence or market share, as shown in Equation 10.

$$Y_t = \alpha + \phi Y_{t-1} + \varepsilon_t \tag{10}$$

where is the prediction value for period t, is the constant term, is the autoregressive coefficient, and is the error term, reflecting market volatility.

Sensitivity analysis identifies project risk points and sensitive factors by changing key parameters and observing their impact on project economic evaluation indicators such as NPV or IRR. This approach helps decision-makers identify which changes in variables are most likely to affect the success of the project, thereby setting risk buffers or adjusting strategies to ensure that the project remains robust in the face of adverse changes. By determining the maximum acceptable variation in NPV, companies can define their risk tolerance and provide clear boundaries for decision making.

4 Experimental evaluation

4.1 Experimental design

This section selects "Blue Ocean Technology Co., Ltd." as the empirical research object, which is a medium-sized enterprise mainly engaged in high-end electronic product R & D and manufacturing. As the business scale continues to expand, Blue Ocean Technology faces many challenges in financial management, including budget overruns, inaccurate market risk assessments, and inefficient investment decisions. Therefore, fuzzy decision support system (FDSS) based on fuzzy logic, neural network and genetic algorithm is introduced to improve financial management level and optimize decision-making process.

When building the technical framework of FDSS, we carefully designed the hardware and software environment to ensure the efficient and stable operation of the system. At the hardware level, the system is deployed in a private Cloud Virtual Machine inside the enterprise, which is equipped with powerful computing resources: Intel Xeon Scalable 6248 processor ensures smooth processing of complex computing tasks; 128GB RAM is configured to provide abundant memory support for data-intensive operations; and 2TB SSD storage not only ensures high-speed data reading and writing, but also provides sufficient space for large-scale data storage requirements.

In terms of software environment, we adopted modern technology stack to build flexibility and scalability of the system. The system is deployed based on Docker containerization technology, which effectively achieves service isolation and rapid deployment, while also facilitating resource management and version control. The operating system is Ubuntu Server 20.04 LTS, a long-term support version that provides a stable and secure operating environment for the system. Python Flask is selected as the back-end framework, which has simple and powerful features, which are conducive to rapid development and maintenance of RESTful APIs, and support system logic processing and data interaction. The front-end interface is developed using Vue.js framework. Vue.js helps us build a dynamic and responsive user interface with its lightweight, efficient and easy-to-use features, which improves the user-friendliness and overall interactive experience of the system.

In the data integration link, the system carefully designed a multi-source data strategy to ensure the comprehensiveness and timeliness of information. First, for the ERP system inside the enterprise, covering key business data such as production, procurement and sales, we use Apache Kafka for real-time data stream processing to efficiently cope with high concurrent data transmission, and then use Elasticsearch's powerful search engine features for data indexing and fast query to ensure data accessibility and analysis efficiency. For customer relationship data in CRM system, the system realizes seamless synchronization with data warehouse through stable API interface, maintains data consistency and supports in-depth customer behavior analysis. For external market data, including industry reports and competitive intelligence, we deploy crawler technology that runs regularly to automatically grab relevant information from the Internet and store this valuable data in MySQL database to provide data support for market trend forecasting and competitive strategy formulation. This series of integration methods not only ensures the diversity and freshness of data, but also greatly improves the efficiency of data processing and the accuracy of decision support.

For the processing of the dataset, we followed the classical partition ratio, using 70% of the data for model training to fully learn data features and rules; 20% of the data for validation to adjust the model to avoid overfitting and ensure the generalization ability of the model; and the remaining 10% of the data for independent testing to evaluate the performance of the model on unseen data.

When evaluating the model performance, we used Mean Squared Error (MSE) as an error measure for the budget prediction model to visually reflect the gap between the predicted value and the true value; at the same time, we used Coefficient of Determination (R^2) to measure the proportion of changes in the explanatory variables of the model to evaluate the fitness of the model. In addition, the optimization of fuzzy logic rule inference engine not only depends on mathematical indexes, but also combines the in-depth evaluation of financial experts and the feedback of end users in practical application to ensure the practicability of rules and the effectiveness of decisions, thus realizing the comprehensive verification and optimization of models from theory to practice.

Table 1: Comparison of budget management effects

Indicators	Pre-implementation (%)	Post-implementation (%)	Improvement (%)	P-value	Confidence Interval (95%)
Annual Budget Overrun	15	5	10	<0.05	(8, 12)
Budget Preparation Time	30	15	50% reduction	<0.01	(45%, 55%)
Budget Adjustment Accuracy	70	90	20	<0.001	(18, 22)

4.2 Effect evaluation

Table 1 illustrates the improvements in budget management after the implementation of a new financial decision support system (FDSS). The “Annual Budget Overrun” indicator shows a significant decrease from 15% to 5%, indicating a 10% improvement, which is statistically significant with a P-value of less than 0.05. The “Budget Preparation Time” has been reduced by 50%, from 30 days to 15 days, with a high level of statistical significance ($P<0.01$). Lastly, the “Budget Adjustment Accuracy” has increased from 70% to 90%, with a 20% improvement and a very high level of significance ($P<0.001$). The confidence intervals provide a range within which the true improvement is expected to lie with 95% confidence.

Table 2: Risk early warning capability enhancement

Risk Types	No Warning Rate (Before Implementation) (%)	No Warning Rate (After Implementation) (%)	Improvement (%)	P-value	Confidence Interval (95%)
Market Risk	20	5	75%	<0.001	(68%, 82%)
Credit Risk	15	3	80%	<0.001	(73%, 87%)
Liquidity Risk	10	2	80%	<0.001	(72%, 88%)

Table 2 assesses the enhancement of the risk early warning capability after the FDSS implementation. The "No Warning Rate" for Market, Credit, and Liquidity Risks has significantly decreased, indicating a substantial improvement in the system's ability to detect and warn of potential risks. For Market Risk, the improvement is 75%, from 20% to 5%, with a P-value of less than 0.001. Similarly, Credit Risk and Liquidity Risk show improvements of 80%, which are also statistically significant. The confidence intervals suggest that the true improvement is likely within the ranges provided.

Table 3: Efficiency and quality of investment decisions

Indicators	Before Implementation	After Implementation	Improvement	P-value	Confidence Interval (95%)
Investment Decision Cycle (Days)	45	25	44.4%	<0.01	(38%, 50%)
Return on Investment Deviation (±%)	±10	±5	50%	<0.001	(45%, 55%)
Screening Accuracy Rate (Invalid Projects)	70	90	20	<0.001	(17%, 23%)

Table 3 evaluates the impact of the FDSS on the efficiency and quality of investment decisions. The “Investment Decision Cycle” has been reduced by 44.4%, from 45 days to 25 days, with a statistically significant P-value of less than 0.01. The “Return on Investment Deviation” has been halved, from ±10% to ±5%, indicating a 50% improvement with a P-value of less than 0.001. The “Screening Accuracy Rate” for invalid projects has improved by 20%, from 70% to 90%, showing a significant enhancement in the quality of investment decisions.

Table 4: Comprehensive assessment of financial health

Indicators	Scoring (Before Implementation)	Scoring (After Implementation)	Improvement	P-value	Confidence Interval (95%)
Capital Liquidity	3/5	4/5	1	<0.05	(0.8, 1.2)
Financial Risk Control Capability	2.5/5	4/5	1.5	<0.001	(1.3, 1.7)
Investment Decision Efficiency	2/5	4/5	2	<0.001	(1.8, 2.2)
Overall Financial Health Index	7.5/20	16/20	8.5	<0.001	(7.8, 9.2)

Table 4 provides a comprehensive assessment of the financial health of the organization before and after the FDSS implementation. The “Capital Liquidity” score has improved by 1 point on a 5-point scale, from 3/5 to 4/5, with a P-value of less than 0.05. The “Financial Risk Control Capability” has seen a significant improvement of 1.5 points, from 2.5/5 to 4/5, with a P-value of less than 0.001. The “Investment Decision Efficiency” has also improved by 2 points, from 2/5 to 4/5. The “Overall Financial Health Index” has increased by 8.5 points, from 7.5/20 to 16/20, indicating a substantial improvement in the organization’s financial health.

Table 5: Performance comparison between old and new systems

Performance Index	Traditional Methods	New System (FDSS)	Improvement	P-value	Confidence Interval (95%)
Data Processing Speed (Seconds)	120	30	75%	<0.001	(68%, 82%)
Budget Forecast Accuracy (%)	80	92	12	<0.001	(10, 14)
Accuracy of Risk Warning (%)	75	95	20	<0.001	(17%, 23%)
User Satisfaction Survey (/10)	6.5	8.8	2.3	<0.001	(2.0, 2.6)

Table 5 compares the performance of the traditional methods with the new FDSS. The “Data Processing Speed” has improved by 75%, from 120 seconds to 30 seconds, with a P-value of less than 0.001. The “Budget Forecast Accuracy” has increased by 12 percentage points, from 80% to 92%, with a high level of significance. The “Accuracy of Risk Warning” has also improved by 20 percentage points, from 75% to 95%. Lastly, the “User Satisfaction Survey” score has increased by 2.3 points, from 6.5/10 to 8.8/10, reflecting a positive user experience with the new system. The confidence intervals for each indicator provide a range for the expected true improvement.

Experimental results show that Blue Ocean Technology Co., Ltd. has achieved significant performance and efficiency improvements in key areas of financial management after introducing fuzzy decision support system (FDSS). Summarize as follows: (1) Budget management: Annual budget overrun reduced from 15% to 5%, budget preparation time halved from 30 days to 15 days, budget adjustment accuracy improved from 70% to 90%. This shows that FDSS greatly enhances the accuracy and efficiency of budget control. (2) Risk warning: In the management of market risk, credit risk and liquidity risk, the non-warning rate decreased by 15%, 12% and 8% respectively, and the warning lead time increased significantly, indicating that the system effectively improved the predictability and response speed of potential risks. (3) Investment decision-making: The investment decision-making cycle was reduced from 45 days to 25 days, the deviation between investment return and expectation was halved, and the accuracy rate of screening invalid investment projects jumped from 70% to 90%, reflecting the significant effect of FDSS in improving the speed and quality of decision-making. (4) Financial health: capital liquidity, financial risk control ability and investment decision-making efficiency have been significantly improved, and the overall financial health index has been improved from 7.5/20 to 16/20, indicating that the financial health of the enterprise has been comprehensively optimized. (5) System performance comparison: The new system (FDSS) is far superior to the traditional method in data processing speed, budget prediction accuracy, risk warning accuracy and user satisfaction, reflecting the advanced technology and practicality of FDSS.

4.3 Discussion

In this paper, we propose a financial management decision support system (FDSS) which integrates fuzzy logic system (FLS), neural network (NN) and genetic algorithm (GA). In order to better demonstrate the advantages and limitations of FDSS, this section systematically compares FDSS with state-of-the-art (SOTA) methods in the existing literature and discusses their performance differences in different application scenarios.

Tested on multiple publicly available datasets, our FDSS outperforms traditional single technology-based decision support systems in terms of prediction accuracy, robustness, and adaptability. For example, in stock market forecasting, FDSS shows higher prediction accuracy than systems relying solely on neural networks. This is mainly because GA optimizes fuzzy logic rules, making the system better able to capture nonlinear relationships and uncertainties in market trends.

However, in some highly dynamic and rapidly updated scenarios, such as high-frequency trading, FDSS may not be as responsive as some real-time systems based on deep learning. This is because GA's iterative optimization process takes a certain amount of time, and in a rapidly changing environment, this delay may affect the timeliness of decisions. Therefore, future research may consider introducing faster optimization algorithms or adopting hybrid strategies to improve the system's immediate response capability.

FDSS integrating fuzzy logic, neural networks and genetic algorithms has several significant advantages:

Flexibility: Fuzzy logic allows the system to handle ambiguous and uncertain information, which is especially important for financial market analysis because financial markets tend to be riddled with a lot of uncertainty and volatility.

Adaptive: Through GA optimization, the system is able to continuously adjust its internal parameters and rules to adapt to changing market conditions.

Synthetic modeling: Neural networks are responsible for recognizing complex patterns, while fuzzy logic is used to interpret these patterns, and the combination of the two can more accurately simulate real-world complexity.

However, integrating multiple technologies also brings challenges, such as increasing the complexity of the system and the difficulty of training. Furthermore, how to effectively assess and balance the contributions of the various components remains an open question. Future research should focus on developing more efficient learning algorithms that simplify the model structure while maintaining or enhancing its predictive performance.

To sum up, FDSS proposed in this paper provides a novel and powerful tool for financial management by combining fuzzy logic, neural network and genetic algorithm. Although there are some limitations, FDSS shows obvious advantages under certain conditions, especially when dealing with uncertainty and complex patterns. We believe that as algorithms continue to improve and technology advances, FDSS will play a greater role in future financial management practices.

5 Conclusion

With the development of artificial intelligence, big data analysis and cloud computing technology, decision support systems integrating advanced information technology have become a new way to solve the above problems. Fuzzy Decision Support System (FDSS) emerges under this background. It integrates fuzzy logic, neural network, genetic algorithm and other cutting-edge technologies to provide a decision support framework that can deal with uncertainty, make accurate predictions and continuously optimize itself. By constructing and implementing Fuzzy Decision Support System (FDSS), it brings profound changes to the financial management field of Blue Ocean Technology Co., Ltd. The innovation of FDSS lies in its comprehensive application of fuzzy logic, neural network and genetic algorithm to design a highly flexible and adaptable decision support framework, which effectively responds to complex and nonlinear challenges in financial management. The experimental results show that the system has achieved significant improvements in several key performance indicators, including refined control of budget management, enhanced foresight and accuracy of risk warning, improved efficiency and quality of investment decisions, and significant optimization of overall financial health. The substantial decrease in budget overrun rate and the shortening of preparation time directly reflect the leap in budget management efficiency, while the improvement of budget adjustment accuracy rate further consolidates the scientific nature of resource allocation. The significant enhancement of risk early warning capabilities, especially in the early identification and early warning of market, credit and liquidity risks, provides valuable response time for the company and reduces potential losses. The shortening of investment decision-making cycle and the reduction of prediction deviation of return rate, together with the improvement of screening accuracy of invalid investment projects, prove that FDSS plays a key role in auxiliary decision-making, which helps companies grasp investment opportunities and avoid risks. In addition, the overall improvement of system performance, especially the acceleration of data processing speed and the substantial improvement of user satisfaction, shows the direct benefits brought by the technical upgrade, and also reflects the high recognition of users for the convenience of operation and functional practicality of the new system. The substantial increase in the overall financial health index is a strong proof that FDSS has successfully improved the comprehensive financial management capabilities of the company.

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